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Sara Biancini

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Abstract

We analyze the demand and supply characteristics of the Indian telecommunications market, in order to assess the potential effectiveness of universal access policies in developing countries. We provide some empirical evidence on the supply and demand characteristics, using a small time-series-cross-section dataset on Indian States. We suggest that the price elasticity of demand for mainlines might be sensibly higher than the levels usually found in developed countries, while the crucial role of income and other sociodemographic variables seems to be confirmed. We also study the impact of cellular penetration, identifying a (positive) network effect in low penetration areas and some evidence of substitution (displacement) in the most developed ones. We finally analyze the supply side of the market, trying to assess the impact of market competition on investment: competition seemingly helps stimulating investment in the most developed areas, but has probably no significant impact in the less developed ones.

JEL-Code: L96, L51, O12.

Keywords: telecommunications demand, universal service, competition, developing countries, India.

Sara Biancini
University of Cergy-Pontoise
33, boulevard du Port
95011 Cergy-Pontoise Cedex
France
sara.biancini@u-cergy.fr

1 Introduction

In most countries, including many developing countries, universal access to telecommunications is considered as an important goal of public policy: universal access and universal service instruments are used to promote access at affordable and non discriminatory prices, independently of local cost conditions. These policies are justified on different grounds.[1] The most important is the existence of network externalities: the larger the network, the bigger the value of the service for each subscriber. It is not clear, though, that this kind of externality could not be internalized by the operators without public intervention (for instance, Crandall and Waverman, 2000 clearly dispute this view). Another argument in favor of universal service policies is based on the identification of telecommunications services as merit goods. Access to telecommunications can reduce exclusion and increase the opportunities of people (reducing the so called "digital divide"). For this reason, access to telecommunication infrastructure should be granted to all citizens. A third argument sees telecommunications as an instrument for regional development, especially for rural and remote areas. This last point is potentially very important in developing countries and it completes the standard externality argument. Telecommunications may have an impact on firm productivity, education and thus economic growth.[2]

In practice, universal service policies or obligations are usually based on some form of cross-subsidization. Historically, telecommunications have been mostly provided by monopolies under regulated price structures. Cross subsidies were implemented in order to provide the service at a subsidized rate to high cost consumers. In liberalized markets, the use of subsidization becomes more complicated. First, competition itself reduces the scope for cross subsidization (because of "cream skimming" in the more profitable segments of the markets). Second, cross subsidies have undesirable efficiency properties (distorting consumption and investment behaviors) which conflict with the development of well functioning competitive markets. Nonetheless, from a theoretical point of view, cross subsidies may still be a powerful tool for financing universal service under competition in developing countries (Gasmi et al., 1999, 2000).

The main critic to universal service policies is that they usually tax the most elastic segments of the market (long distance, mobiles) to provide subsidized access (which is thought to be very inelastic). This introduces important distortions in the economy, which have to be compared with the benefits associated to the policies. Indeed, the desirability of universal service policies depends both on demand and supply characteristics. In particular, if access demand is very inelastic, subsidized access has a very low impact, which has to be compared to the possibly high distortions introduced (see Hausman et al., 1993 and Hausman, 1998). Moreover, the supply side is also important. Private competition can also contribute to lower prices and increase access, reducing the need for direct public intervention. For instance, Clarke and Wallsten (2002) argue that liberalization has been much more beneficial than cross-subsidization policies in developing countries, also toward the poor. Then, the desirability of universal

[1]For a review of the theory of Universal Service provision, see Cremer et al. (1998).

[2]Roller and Waverman (2001) estimate the impact on GDP of telecommunications investment, adopting a simultaneous equation model on a panel of OECD countries. They find a positive effect of telecommunications on growth. They also identify a critical mass effect: the positive impact on growth is larger when the diffusion of telecommunication is close to universal service (as in developed countries). Following Roller and Waverman (2001), Sridhar and Sridhar (2004) estimate a similar model on data from non-OECD countries: they also find a positive effect on growth. Moreover, Waverman et al. (2005) show that, when considering mobile telephones, the growth dividend is even larger in developing countries. In a recent paper, Jensen (2007) provides extensive evidence that the diffusion of mobile telecommunication services among Kerala fishermen has improved both market performance and total welfare.

access policies is ultimately an open empirical question. It depends on demand characteristics (elasticities) as well as supply characteristics (effect of competition and other market conditions).
Unfortunately, most of the existing empirical evidence concerns developed countries, due to the larger availability of data. In these countries, the penetration of telecommunication infrastructure is close to saturation. There are reasons to think that the relevant elasticities (e.g. price elasticity) could be different in less developed countries. Similarly, the importance of network externalities and the related market failure could be larger at the first stages of diffusion. Finally, the role of the mobile technologies could be different in developing countries, which started developing their telecommunications sector recently and are confronted with different technological options. The existing empirical evidence on developing countries is limited: the present paper aims to add a contribution in this sense. India is an appealing candidate for this kind of analysis. It is a low income country which experienced an impressive development of telecommunications. Moreover, India is a federation of States with fairly different socioeconomic conditions. This allows us to apply panel data techniques on homogeneously collected data. Unfortunately, the existing data do not allow to perform sophisticated empirical analysis. Nonetheless we can estimate simple models in a small cross-section-time-series data set and show some preliminary results which add to the debate on universal service and universal access.

The paper proceeds as follows. After briefly presenting the related empirical literature and the main features of the Indian market for telecommunications, we analyze the characteristics of demand for fixed lines (Sections 2 and 3). Our econometric analysis suggests that price elasticity in developing countries might be sensibly larger than the usual estimates, sustaining the idea that subsidized access might be much more effective in developing countries than in developed one. Moreover, the diffusion of mobile telephony seems to have different effects in different regions. In the less developed ones, the diffusion of mobiles has a positive impact on the diffusion of fixed lines, while in the more developed ones there is some evidence of substitution (i.e. mobile telephones start acting as a displacement technology). These results are confirmed using an alternative specification based on the logistic diffusion model (Section 4). In the last part of the paper (Section 5), we estimate a simplified supply equation trying to capture the effect of competition on infrastructure investment. This last exercise gives us some preliminary insights on the supply side of the market and the potential for market driven development of the sector.

1.1 The Related Empirical Literature

Most of the existing studies estimating telecommunication access demand and the potential distortions associated with universal service instruments are centered on the United States (for a discussion see Riordan, 2002). Due to the federal structure of the country and the huge availability of data, accurate estimations of telecommunication demand has been performed by several authors. In particular, the results by Kaserman et al. (1990), Hausman et al. (1993) and Hausman (1998) opened a debate on the effectiveness of universal service policies and the distortions introduced by industry taxes in the US telecommunication sector. They show that access demand has a very low elasticity and thus the subsidies aimed to increase penetration have almost no impact. Even worse, they are likely to be socially inefficient because they tend to tax the more elastic segments of the market (long distance, mobile telecommunications) in order to cross subsidize access (see also Eriksson et al., 1998 and Garbacz and Thompson, 1997). Garbacz and Thompson (2002, 2003) performed a demand estimation based on decennial Census data, with similar conclusions. In a more recent work, Ackerberg et al. (2008) concentrate directly on low-income demand for telecommunication services, carefully taking into account for the possibility of endogenous determination of the policies. They find a higher elasticity of access demand than previous studies and argue that the impact of universal service policies may have been underestimated. Following this contribution, Garbacz and Thompson (2009) have re-estimated their previous model adjusting for endogeneity. They find an increase in the impact of targeted subsidization programs. However, they can still conclude that programs designed with the intent to increase telephone penetration are increasingly less effective and more expensive.

Garbacz and Thompson (2005) have extended the approach developed in their previous studies to a panel of developed and developing countries. In both cases, they find a non significant price elasticity of access for fixed lines, questioning the effectiveness of USO policies focused on subsidized access. Similarly, Garbacz and Thompson (2007) concentrates on less developed countries, finding a significant but still very small elasticity of the connection charge and no significant elasticity of the monthly charge. Then, the few existing studies seem to agree on the fact that access price elasticity remains very low also in developing country. Contrarily to these findings, we find some preliminary evidence that price elasticity might be higher than the one obtained in the previous studies.

Some of the cited papers also investigate the relationship between fixed and mobile technology. For instance, Garbacz and Thompson (2007) suggest a current complementarity of mobile and fixed services in developing countries. This is consistent with the findings of Garbacz and Thompson (2003) for the United States and Ahn and Lee (1999) for a panel of 64 Countries. A bunch of other studies have analyzed the substitutability between fixed and mobile phones applying the logistic diffusion approach. Gruber and Verboven (2001) study the development of mobile services in the European Union. The estimated impact of the fixed network on the diffusion of mobiles is negative. On the contrary, in the estimation made by Gruber (2001) to a panel of Central and Eastern European countries a positive effect is found. More recently, Madden and Coble-Neal (2004) and Rouvinen (2006) estimate two Gompertz diffusion models on panels of heterogeneous countries. Madden and Coble-Neal (2004) separate the network effect from the pure substitution in usage. They show that the development of fixed lines has a positive effect on the diffusion of cellular phones (positive network effect), but the cross-price elasticity is positive (the two modes of communications are substitutes in usage). Rouvinen (2006) find evidence of network effects and complementarity.

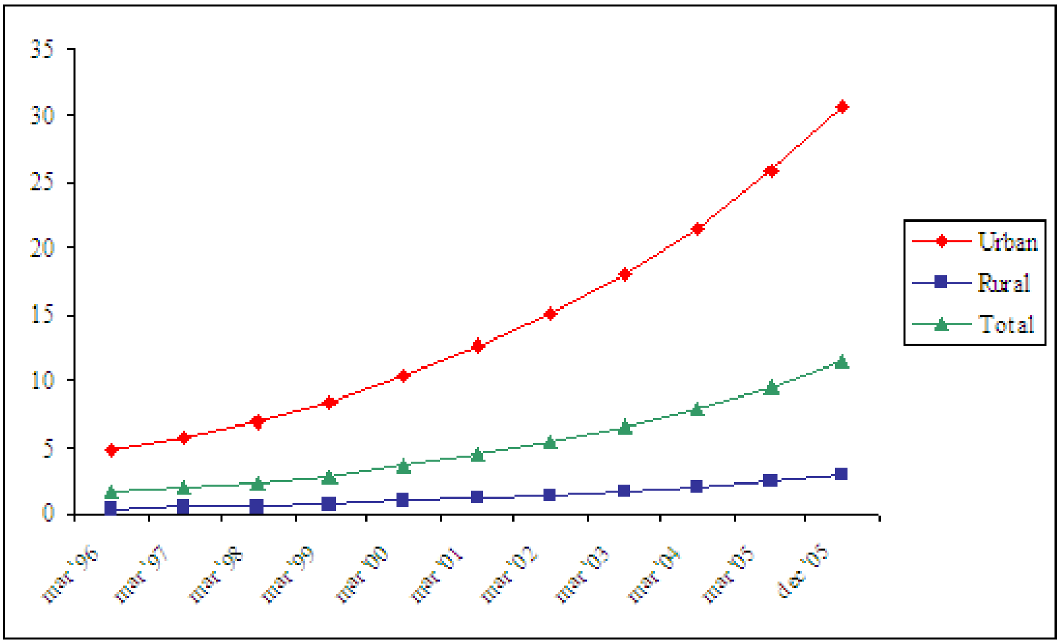
These heterogeneous results suggest the relation of complementarity or substitutability between fixed and mobiles phones is not necessarily the same in all countries. In some developing countries, the supply side constraints associated with the inefficiency of the incumbent fixed lines operator may induce households to choose a mobile connection. For instance, anecdotical evidence shows that in many African countries mobile phones are a substitute for fixed lines, even in poor and rural villages. This is also supported by econometric evidence presented in Waverman et al. (2005) for a panel of African and non African middle-income countries (see Waverman et al., 2005). We consider this issue for the case of India investigating the effect of mobile phones in different areas at different levels of telecommunications and overall development. This allows us to give some insights on the relationship between fixed and mobile telephones diffusion at different stages of development.

1.2 Telecommunications in India

Telecommunications reforms in India started in 1991, when the Government announced the beginning of private participation to the industry. The actual entry of private operators began some years later, around 1995/96. In order to issue the licences, the Indian market was divided into 23 separated areas (Telecommunications Circles), which roughly correspond to States, groups of small States or big metropolitan areas (Delhi, Mumbai, Kolkata and Chennai). The metropolitan areas are treated separately and classified as Metros. The other areas divided three categories on the basis of the perceived revenue potential (Circles of type A, B or C respectively). Initially, the market was organized following a duopoly policy in which the incumbent was largely dominant. In this period the telecommunications sector began to grow, after a long stagnation. The first years of private participation were quite turbulent, with litigations arising from the difficulties encountered by the private entrants in honoring the payment of licences. In 1999 the New Telecommunication Policy (NTP) was announced: it shifted the licence regime into a revenue share agreement and gave new authority to the regulator (TRAI), which was also put in charge of price regulation. The following year the public incumbent BNSL was corporatized and the duopoly policy abandoned in favor of more competition. In addition, a rationalization of the interconnection policy boosted the development of cellular telephony. The scope for Universal Service was enlarged and the increase in rural teledensity began a priority. This is the period in which Indian telecommunications started experimenting extraordinary rates of growth. Between 2002 and 2005 the total number of telephones increases from 30 to 104 millions. Interestingly, most of the growth was due to and increase in mobile connections, which passed from 6.4 to 57.4 millions (Noll and Wallsten, 2005). It is difficult though to quantify to which extent this growth of mobile connections reaches uncovered households (Malik and De Silva, 2005). It is then crucial to try and understand if mobiles are a displacement technology with respect to fixed lines, especially in these areas that are lagging behind and constitute the natural target of universal service policies. When looking at total teledensity (fixed and mobile connections), we observe that the gap between urban and rural teledensity has steadily increased: the benefits of telecommunications growth seem to be mainly captured by wealthier and urban customers (see Figure 1).

The Indian government and regulator are increasingly concerned with the difficulties of promoting the universal service goals announced in the National Telecommunication Policy. The current policy instruments are two different taxes: the Universal Service levy and the Access Deficit Charge (ADC). The first is paid as a percentage of the revenue earned by the various operators. The second is mainly paid by private operators to the incumbent for providing access in rural areas at a subsidized rate. The existing policies, and especially the ADC, have been widely criticized for their inefficiency properties by many observers (see for instance Noll and Wallsten, 2005). Moreover, the association of Indian telecom providers (AUSPI) and other observers have expressed concerns about the high level of taxes on the Indian telecommunication industry, which could be an obstacle to further growth of the sector. However, prices in India remain relatively low, if compared to the one prevailing in other countries

Figure 1: Total Teledensity (source: TRAI)



with similar socioeconomic characteristics. The extent to which the current level of prices and the subsidized access policy can influence diffusion depends on demand characteristics that have to be estimated (price elasticity, diffusion of mobile phones). Our analysis aims to shed some light on the determinants of demand and investment behaviors, helping to evaluate the plausible impact of subsidized access policies, market reforms and the diffusion of mobile telephony.

Previous work on fixed telephony demand in India has been done by Das and Srinivasan (1999). They give an estimation of price elasticities and their data also allowed to distinguish between local and long distance calls price elasticities. Their estimation of the price elasticity of aggregate telephone usage is comparable to the ones in the present paper, but somehow smaller. The present paper, based on more recent data, extends and completes their analysis, taking into account the effect of more recent reforms and exploiting the information contained in the new market organization (the Circles classification). Moreover, our data allow to study the impact of the recent diffusion of mobile telephones on the deployment of fixed-lines.
More recently, econometric work on Indian telecommunications has been done by Narayana (ming, 2009). These papers present evidence based on survey data collected in 2003 for the State of Karnataka. Narayana (2009) shows that education, income and castes are important explanators of telecommunications demand.[3] Using State-level panel data on all Indian States, the analysis confirms the importance of income, literature and castes. In addition, it shows that price elasticity is a significant and rather important explanator of fixed-lines demand. This is consistent with the findings of Narayana (Forthcoming), which finds that usage price is a highly significant explanator of

[3] He also distinguishes between rural and urban demand, showing that education and castes are somehow less important in rural areas.

telecommunications demand. The evidence confirms that price elasticity is likely to be very significative, and its impact might be larger than previously thought. Narayana (Forthcoming) also explores the relationship between fixed and mobile technologies and finds a substitution effect. This result is consistent with the findings in the present paper for the more developed telecommunication Circles, such as Karnataka. However, it will be shown that, in the less developed areas, an inverse relationship can arise, due to positive network externalities between fixed and mobile telephones.

1.3 The data

We build a small cross-section-time-series dataset using several Indian institutional sources. To assess demand and supply characteristics, we need data on telecommunications diffusion and prices as well as socioeconomic and market indicators. As often with less developed countries, some of these data are difficult to find. For all telecommunications variables, we use data from the Department of Telecommunications (DOT) of India Annual Reports from 1994 to 2004 and from the International Telecommunication Union (ITU). They also contain some demographic variables such as population and population density (population per square kilometer). Other sociodemographic variables are constructed using the information contained in the decennial Census surveys.[4] Data on competition are collected by the Indian Regulator TRAI. Finally, some data on investment (capital outlays) are published (only) by the incumbent operators (BNSL and MTNL): the series from 1998 is available at *http://www.indiastat.com*. As an alternative measure of the level of investment, we use the equipped capacity of the exchanges, which is also available for the private undertakings.

These data as several problems. The first is that our dataset is very small and does only allow to estimate simple models. Moreover, some of the available data are admittedly only proxies of the economic variables we would ideally use in our econometric analysis. In this respect, the main problem is that the only available measure of the price level is the average revenue per line. This is clearly not very satisfactory, but we could not find an alternative (Waverman et al. (2005) have the same problem). Moreover, no price index is available for mobile telephony, limiting our analysis on the relationship between the two technologies.

On the bright side, the existing data are all collected homogeneously by the national statistical offices and institutions, reducing the omitted variable bias which is sometimes important in cross-countries analysis. Moreover, even this small dataset fortunately allow us to give some insights on phenomena we try to explain. More details about the data and their limitations are given when the variables and the estimation methods are introduced.

2 The demand for mainlines

We start our analysis on the demand for telecommunications in India estimating a linear demand equation. At this stage, we use the number of main lines per 100 population as a proxy for service penetration. This is of

[4]Because of their slow dynamics, the annual values have been reconstructed interpolating the available decennial trends. We considered the possibility of adding data from the National Sample Surveys. They are collected in different years but they are not directly comparable to Census data, especially in reason of smaller samples. For this reason, they have not been included in the series.

Table 1: Variable Description and Sources

Name	Description	Source
del	direct exchange lines per 100 people	DOT
wl	waiting lists per 100 people	DOT
pen	direct exchange lines + waiting list per 100 people	DOT
hpen	household penetration (% of households with a fixed line in 1999)	DHS+
p	average revenue per direct exchange lines in real prices	DOT
month	monthly subscription in real prices	ITU
cellpen	cellular penetration (cellular phones per 100 people)	DOT
area	State area in square kilometer	Census
ruraldel	share of rural direct exchange lines	
density	population per square kilometer	DOT
y	per capita real gross domestic product in real prices	Indiastat
liter	literacy rate	Census
castes	rate of population in scheduled castes or tribes	Census
capacity	total capacity of local public switching exchanges	DOT
comp	number of competitors	TRAI
compcell	number of mobile phone providers	TRAI
inv	capital outlays (BNSL) in real prices	Indiastat

course not completely satisfactory because this does not correspond to household penetration or even residential lines. However, since main lines are reported on yearly basis in most countries, this allows us to have a fist assessment of the determinants of demand and to compare it with the existing studies. As standard, we assume that demand for telephone mainlines is a function of price, income and other variables controlling for living conditions.

$$\log(pen_{it}) = \beta_0 + \beta_1 \log(p_{it}) + \beta_2 \log(y_{it}) + \beta_3 X_{it} + \varepsilon_{it}$$

The left hand side variable pen is given by the sum of main lines and waiting list (per 100 people). The inclusion of waiting lists tries to capture some of the demand which is not satisfied due to supply side constraints (unfortunately, some of the demand is probably completely discouraged in case of very poor supply, but we cannot control for that). p is the indicator of the price level, y is per capita income and X is a vector of control variables (sociodemographic characteristics and, possibly, fixed effects and time dummies). All variables are taken in logs (excluding dummies) and the coefficient can be interpreted as elasticities. As mentioned in Section 1.3, as a proxy for the level of the price p we use the average revenue per main line. This raises a clear problem of endogeneity: we try to reduce the bias introduced by this problem with a simple instrumental variable strategy which is discussed below.[5] Other explanatory variables are population density ($density$) and sociodemographic variables such as the literacy rate ($liter$) and the percentage of inhabitants belonging to scheduled castes and tribes ($castes$).

[5] In Section 1, we mentioned that the diffusion of telecommunications services can have a positive impact on growth. This may raise an endogeneity problem also for the regressor y. For this reason, we also run all regressions removing y and alternatively replacing it with the share of population which has access to electricity (access to electricity is highly correlated with the level of life): this does not modify our

Population density is used to capture the access externality that flows form potential subscribers in a given area, and can then be interpreted as the value of accessing a network of subscribers (access externality). Indeed, population density has been used to measure the access externality in most of the existing studies, such as Crandall and Waverman (2000) and in the works of Garbacz and Thompson (2002,2005,2007). The same strategy is adopted here, which facilitates comparison of our results with the previous literature. On the other hand, Riordan (2002) note that this strategy may have some limits because population size and density are positively correlated. It is then possible that $density$ is picking up two contrary effects, the local network externality effect, and a face-to-face communication effect. For this reason, Riordan (2002) also controls for the population size. This possibility was also tested, but the results were not significantly affected.[6]

Literacy rates have been used in several study to capture the level of life which, especially in developing countries, is often not well described by per capita GDP. Scheduled castes and tribes register people traditionally considered "outcastes" (also called "untouchables"), relegated to marginal occupations and victims of social exclusion. These groups are now accorded a special status under the Constitution, trying to reduce their socioeconomic disadvantage. The percentage of people belonging to scheduled castes and tribes can be interpreted as a proxy for poverty, describing the impact of belonging to less favored segments of the population. This is also a rough way to distinguish minority ethnic groups, which may have different consumption behaviors.

In India, the basic tariffs (access, monthly rent) are regulated at the central level. This reduces the problem of price endogeneity (these tariffs are not subject to idiosyncratic shocks at the State level). However, the average revenue per line does not depend only on these tariffs, but also on the patterns of usage and the different tariff plans, which we cannot observe. To try reduce the endogeneity bias, we estimate an instrumental variable regression in which the price is endogenous. The available data make it difficult to build instruments for the price. We can just use some cost proxy as well as market conditions for the identification strategy. Unfortunately, our small database does not allow to use more sophisticated procedures such as the Arellano-Bond/Blundell/Bover system GMM estimators, which use the entire set of lagged values of the dependent and of the other endogenous covariates as instruments. With our small database, the model collapses and no sensible estimate of the parameters can be obtained. We then turned to a simple instrumental variable regression, in which the first stage equation predicts the value of the price from a regression on cost proxies, policy indicators and competition measures.[7] In the second stage, the demand estimation is performed. The first instrument we use is the rural percentage of existing lines ($ruralshare$). This can first be interpreted as a cost proxy. Interestingly, price regulation at the national level imposes different tariffs for the rural areas. This tariffs are decided at the central level and homogeneous across the country (they are the same in all States): for this reason, the rural share is not only a cost proxy, but it embodied an an exogenous constraint on the revenue per line, independent of State-level idiosyncratic conditions. A second cost proxy is given

findings. When removing y, the coefficient of the other indicators of the level of life (literacy rate, share of population in scheduled castes) increase, but the main results of the analysis are preserved.

[6] In the same spirit, Garbacz and Thompson (2002) also test the impact of an externality variable defined as "penetration times the number of households". The introduction of an externality variable of the same kind (defined as $pop * (cell + pen)/100$) has been checked and it does not change the main findings.

[7] The use of a set of instruments of this nature is quite standard in this literature, although market reforms themselves might be endogenous. In our case, this concern is not an issue, because the telecommunication policies are decided at the central level and introduced at the same time in all Circles. However, this annuls the cross section variability. The effective development of competition (number of entrants) has cross section variability. However, because the issuing of licences was made only in some years (the same for all States) time variation is small.

by the investment cost per line (inv/del). As for the market structure and market reforms variables, we include a dummy for the NTP (i.e. equal to 1 for the years following 1999), the number of competitors in basic services[8] and interactions between the number of competitors and the NTP. The reasoning for introducing interactions is that, as explained in Section 1.2, before the application of the National Competition Policy, the extent of effective liberalization was very limited and the competitor largely dominant. We would expect competition to reduce prices. However, competition can be associated with increasing quality/variety and consequently with increasing prices. Moreover, entry may be driven by unobservable profitability characteristics which are also correlated to the demand for new lines. For this reason, we also control for the circle types, introducing circle-classification dummies, controlling for unobservable profitability characteristics.[9] Moreover, we interact the number of competitors with the Circles dummies, allowing for different impacts in areas with different market conditions. The first stage regression confirms our intuitions.[10] Competition (entry) alone has no significative effect on prices. A significative and negative effect of entry on prices is founded interacting $comp$ with the circle types, but only for low penetration Circles. In the most profitable Circles entry is not associated with a significative price reduction, probably because of unobservable increases in the quality or variety of the services. $ruralshare$ has a negative impact on the price, which would mean that it is not measuring costs, but rather exogenous negative impact on the rentability of lines. On the contrary, inv seems to be capturing cost proxies, increasing the price measure. The results of the first stage regression are given in Table 2.

Table 2: Price Regression (First Stage)

variable: p	
rural share	-0.180^{***}
	(0.026)
inv/del	0.194^{***}
	(0.039)
NTP	-0.205^{***}
	(0.043)
comp	0.093
	(0.057)
comp*NTP*circle-A	-0.091
	(0.060)
comp*NTP*circle-B	-0.001
	(0.060)
comp*NTP*circle-C	-0.161^{**}
	(0.084)

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 3 illustrate the estimation results of the different models. The basic OLS regression is given in Column (1). The price elasticity is estimated at -0.397 and income and sociodemographic variables appears important in explaining demand for main lines.

[8]Because mobile providers may also exert a competitive constraint on mainline operators, we also estimate an alternative specifications using the number of mobile competitors, with very similar results

[9]Because all socioeconomic variables are collected at the State level, we use dummy variables for the Circle types (A, B or C respectively) and include the Metros in the Circles of the respective States (Delhi, which constitutes at the same time a separate State and a metro Circle, is put in the same group as the A-Circles).

[10]Although Table 2 only shows the impact of the excluded instruments on the endogenous variables, all exogenous variables have been included in the first stage regression before estimating the demand equation. Standard statistics have been run to evaluate the identification strategy. The Sargan test for overidentification does not reject exogeneity, while the partial R-squared of the exclude instrument is 0.39.

In order to exploit the panel nature of the data, we introduce fixed state effects in order to account for cross section time invariant unobserved heterogeneity. The problem is that the sociodemographic variables display a very little time variation, making it difficult to estimate their impact in a fixed effect specification. Column (2) of the table 3 reports the results of the fixed effect regression. The price elasticity of -0.603. Sociodemographic characteristics are highly non significant and have implausible signs. We then estimate the same model with random effects: the results are presented in Column (3). This gives a price elasticity of -0.723 and reasonable coefficients for the sociodemographic characteristics.[11] In column (4) we introduce fixed effect for the circle types (A, B or C type). This strategy allows to control for differences among heterogeneous groups of States, which share some unobservable profitability and market characteristics. Introducing fixed effects for the Circles allows to introduce meaningful fixed effect and at the same time to estimate the impact of the variables characterized by small time variation. Controlling for these fixed effects, the price elasticity is -0.640 and the magnitude of the other explanatory variables remains comparable. In Column (5) we present the instrumental variable regression: the coefficient for the price is -0.721, sensibly higher (in absolute value) than the OLS. In this estimation, the number of observations is smaller because less observations are available for the chosen instruments.
All our specifications suggest that the price elasticity might be higher than previously thought. Exploiting the panel dimension (fixed and time effects) shows that the OLS regression is biased toward zero. The instrumental variable regression give a more precise assessment of this bias. Contrarily to the findings of Garbacz and Thompson (2005, 2007), our evidence about India, although based on a poorer dataset, seems on the contrary to suggest that access elasticity in less developed countries is somehow higher. Taking into account the fact that tariffs in India are sensibly lower than in other developing countries in the same income group, one could even expect the price elasticity to play a larger role in other developing economies. As in all the existing studies, the importance of income effects is confirmed. All the variables describing the level of life seem to play an crucial role in explaining the demand for telecommunications. The impact of literacy is positive and large. Belonging to scheduled castes or tribes is shown to negatively affect demand for telecommunications access.

We now turn to the question of the impact of mobile telephony diffusion on the development of the fixed network. This is particularly relevant in India, where the growth of mobile telephony in the last years has been impressive. Still, mobile phones are mainly available in metropolitan areas.
Two opposite effects can play. On the one hand, mobile and fixed telephones can be seen as substitutes. On the other, the diffusion of mobile phones can have a positive network externality on fixed lines (this would mean that, although fixed and mobiles might not be complements in for a given consumer, the development of the wireless technology has a positive impact on the diffusion of mainlines). Lacking information about mobile prices at the State level, we cannot really asses the existence of economics substitutability between the two services. However, we can derive some preliminary results on the impact of mobile phones on the diffusion of fixed lines and in particular on the question if mobile telephony represents a displacement technology. In order to do that, we introduce

[11] We perform a panel robust version of the Hausman test for fixed versus random effects.[12] The test does not reject the hypothesis of random effects (at the 5% level). Even if the coefficient estimates are sensibly different in the two estimations, due to the high standard errors the test cannot reject the presence of random intercepts.

Table 3: Demand Estimation

variable: pen	(1)	(2)	(3)	(4)	(5)	(6)	(7)
p	-0.397^{***}	-0.603^{***}	-0.723^{***}	-0.640^{***}	-0.721^{***}	-0.565^{***}	-0.703^{***}
	(0.107)	(0.157)	(0.219)	(0.115)	(0.205)	(0.107)	(0.105)
y	1.181^{***}	-0.700	0.616^{***}	1.031^{***}	0.865^{***}	1.174^{***}	1.082^{***}
	(0.069)	(0.409)	(0.188)	(0.073)	(0.089)	(0.075)	(0.073)
density	0.137^{***}	-1.796^{*}	0.157^{**}	0.104^{***}	-0.036	0.143^{***}	0.117^{***}
	(0.020)	(0.951)	(0.063)	(0.049)	(0.036)	(0.024)	(0.025)
liter	0.734^{***}	0.067	0.986	0.850^{***}	0.995^{***}	0.831^{***}	0.928^{***}
	(0.194)	(0.572)	(0.697)	(0.186)	(0.269)	(0.220)	(0.211)
castes	-0.145^{***}	0.609	-0.073	-0.172^{***}	-0.280^{***}	-0.151^{**}	-0.178^{***}
	(0.052)	(0.498)	(0.236)	(0.049)	(0.050)	(0.058)	(0.053)
cellpen	-	-	-	-	-	0.021^{**}	-
	-	-	-	-	-	(0.009)	-
cellpen*circle-A	-	-	-	-	-	-	-0.012
	-	-	-	-	-	-	(0.011)
cellpen*circle-B	-	-	-	-	-	-	0.028^{***}
	-	-	-	-	-	-	(0.009)
cellpen*circle-C	-	-	-	-	-	-	0.042^{**}
	-	-	-	-	-	-	(0.010)
p endogenous	no	no	no	no	yes	no	no
state-level fixed effects	no	yes	no	no	no	no	no
state-level random effects	no	no	yes	no	no	no	no
circle-level fixed effects	no	no	no	yes	yes	no	no
time dummies	yes	yes	yes	yes	yes	yes	yes
observations	200	200	200	200	114	200	200

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

the level of cellular penetration ($cellpen$) as an explanatory variable in the equation describing the demand for fixed lines. Obviously, this rises new endogeneity concerns. Both measures of service penetration (fixed and mobile) might be correlated with unobservable determinants of telecommunications diffusion. However, we can try to identify the effect of mobile telephones from the gap between different areas, characterized by different telecommunications market characteristics (a similar strategy has been used, in a totally different context, by George and Waldfogel, 2006). In the identification strategy we use again the information captured by the circle classification. This strategy is correct as long as we believe that the unobservable change in fixed lines correlated with $cellpen$ goes in the same direction in low and high penetration Circles. The results of the regression including mobile phones as an explanatory variables are given in Columns (6) and (7).[13] The coefficient of cellular penetration is positive, though rather small. This would indicate that a positive network effect exists at the aggregate level. Unfortunately, the result could be also driven by the endogeneity of $cellpen$. In order to better identify this effect, as mentioned above, we interact the variable $cellpen$ with the dummies for circle types. This is the continuous equivalent of separate estimations of the effect of mobiles for the different groups of Circles, characterized by different stages of market development. We identify the impact of mobiles diffusion from the gap between the propensity to subscribe fixed lines in the different circle types. The positive effect is confirmed in Circles of type B and C, which are the one with lower penetration. Network externalities and complementarities between the services seem to be more important where coverage is poor. On the contrary, for A-Circles the coefficient is negative (but non significant), showing a tendency toward the displacement of fixed lines by mobile diffusion. Unfortunately, from the existing data, it is not possible to study cross-price elasticities in order to address the question of potential substitutability in usage, which plausibly introduce a form of competition between fixed and mobile providers. However, the results of our analysis sheds new light on the impact of cellular telephony at different level of general telecommunication service diffusion.

3 Access demand: a logit specification

In Section 2, we provided a first estimation of demand for main lines. To go from lines to access demand it is necessary to build a variable describing household penetration. Available data include both the number of direct exchange lines and the number of households. The problem is that direct exchange lines does not exactly correspond to subscribers at the household level (and they include business connections). We then use information on household penetration available for the year 1999 in the DH+ Surveys to reconstruct the relationship between direct exchange lines and subscribers (we are forced to assume that this relationship is stable across time, possibly introducing some problem of measurement error). Using this measure of household penetration, we want now to estimate a logit model in which the binary variable is the decision to connect to the network. Formally, the logistic regression model specifies the probability of being connected π as:

[13] In the regression, $cellpen$ appears to be highly collinear with the time dummies starting from year 2000. As explained in Section 1.2, after the New Telecommunication Policy, a change in the access policies favored the diffusion of mobiles. This can explain the existence of two different "time periods". We then replace year dummies with the NTP dummy. Using a time trend gives very close results.

Table 4: Household Access Model

variable: $\log(\frac{\pi}{1-\pi})$	(1)	(2)
p	-0.00006^{***}	-0.0001^{***}
	(0.00003)	(0.00002)
y	0.00007^{***}	0.00007^{***}
	(0.000009)	$(0.00001)^{**}$
density	0.00005^{***}	0.00007^{***}
	(0.00002)	(0.00002)
liter	0.328^{***}	0.432^{***}
	(0.004)	(0.004)
castes	-0.012^{***}	-0.106^{***}
	(0.004)	(0.004)
MCSE	yes	no
MLE	no	yes
time dummies	yes	yes
observations	200	200

*** significant at 1% level, ** significant at 5% level,
* significant at 10% level.

$$\pi_{it} = \frac{\exp^{\beta Z_{it}}}{1 + \exp^{\beta Z_{it}}} \tag{1}$$

Where Z represents the explanatory variables. We use $hpen$ as the measure of household penetration. Explanatory variables include price, income and the other the other controls used in Section 2. In our data, observations are indeed State-level proportions and not household level observations. Logit models with proportions (grouped data) need a treatment of the heteroskedasticity related to within-cell heterogeneity (a cell is here a grouped observation of a proportion at the State level, and not a household level binary variable). Different strategies may be implemented. We apply here two standard estimation techniques: the minimum chi-square and maximum likelihood estimators. The minimum chi-square estimation (MCSE) is given in Column (1) of Table 4.[14]
The maximum likelihood estimation (MLE) is presented in Column (2). Although MCSE and MLE have the same asymptotic properties, they are not equivalent in small samples.[15]

As shown in table (4) the estimated coefficient and standard errors are very closed to the one obtained by MCSE.

In both estimations, the coefficients are interpreted as quasi-elasticities. In the logit model, the derivative of the probability of having telephone service with respect to an explanatory variable x_i is given by:

$$\frac{\partial \pi_{it}}{\partial x_i} = \beta_i \, \pi_{it} \, (1 - \pi_{it})$$

From this expression one can derive the relevant elasticities. Computing the price elasticity at the sample

[14]The estimation is carried using a two-step procedure. We first estimate an OLS model explaining $hpen$ as a function of the explanatory variables. The estimates are then used for computing the weights of the second-stage FGLS estimation, based on the estimated variance of the logit model S_{it}:

$$S_{it} = \frac{1}{n_{it}\hat{\pi}_{it}(1 - \hat{\pi}_{it})}$$

Where n_{it} is the number of households grouped in the aggregate observation for State i at time t.

[15]The log likelihood function for proportion data writes:

$$\log L = \sum_i n_i \log\{hpen_i \log(\pi_i) + (1 - hpen_i)\log(1 - \pi_i)\}$$

mean, we find a coefficient of -0.61. Elasticity is smaller in States with higher penetration and/or in more recent years. The minimum value is as small as -0.17. Consistent with the finding of Section 2, the average values are sensibly higher than the ones estimate for developing countries, but seems to be decreasing when penetration improves. Teledensity is significantly affected by income and other sociodemographic characteristics: income growth and increases in education may boost telecommunications growth. Elasticities with respect to representative variables are given in Table 5.

Table 5: Elasticities

variable	average	min	max	'01-'04
p	-0.61	-1.65	-0.17	-0.40
y	0.75	0.19	1.12	0.75
liter	1.86	1.28	2.55	1.88
castes	-0.35	-1.04	-0.10	-0.33

Elasticities are computed from the maximum likelihood estimations presented in Table 4, Column (3).

Introducing mobile phones penetration, we find again a positive effect in lower penetration Circles (higher in C-Circles). On the contrary, in A-Circles, the impact of mobile on fixed penetration is significantly negative, suggesting that substitution between fixed and mobiles platforms may be going on in the more developed areas.

4 Diffusion of telecommunications: a logistic diffusion approach

The issues related with telecommunication diffusion and network effects present some dynamic aspects which are not captured by the models estimated above. In particular, the individual decision to connect may depend on the size already reached by the network itself as well as on the development of complementary network goods (the diffusion of mobile phones, for instance). Several recent papers study mobile telecommunications diffusion and try to assess the impact of fixed lines on the development of the mobile network (see Section 1.1). Contrarily to these contributions, we look here at the diffusion process governing the fixed lines. We thus characterize the determinants of fixed lines diffusion and the impact of mobile penetration on the development of the fixed network. We assume that telephone penetration tends towards an equilibrium level pen^*, following a logistic process. In theory, both the equilibrium penetration and the shape of the logistic curve might depend on prices, income, socioeconomic characteristics and market conditions. However, such a general specification complicates too much the estimation of the model, especially with a small dataset (see also Gruber and Verboven, 2001 on this point). We thus compare two alternative specifications of the logistic process. In the first specification, the rate of convergence is kept constant, while the equilibrium penetration is assumed to depend on our set of explanatory variables. In the second specification, we specify the market potential as a fixed share of the total population (to be estimated), while the initial state and the rate of convergence are a function of the demand and supply

Table 6: Household Access Model with Mobiles

variable: $\log(\frac{\pi}{1-\pi})$	(1)	(2)	(3)	(4)
p	-0.0001^{***}	-0.0001^{***}	-0.0001^{***}	-0.0001^{***}
	(0.00002)	(0.0002)	(0.00002)	(0.00002)
y	0.00009^{***}	0.00008^{***}	0.00009^{***}	0.00009^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
density	0.00008^{***}	0.00008	0.00008^{***}	0.00009^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
liter	0.303^{***}	0.327^{***}	0.027^{***}	0.029^{***}
	(0.004)	(0.003)	(0.004)	(0.0025)
castes	-0.018^{***}	-0.015^{***}	-0.018^{***}	-0.016^{***}
	(0.004)	(0.004)	(0.004)	(0.003)
cellpen	-0.017	-0.052	-	-
	(0.035)	(0.037)		
cellpen*circle-A	-	-	-0.074^{**}	-0.080^{**}
			(0.032)	(0.027)
cellpen*circle-B	-	-	0.353^{***}	0.335^{***}
			(0.077)	(0.083)
cellpen*circle-C	-	-	0.313	0.473
			(0.479)	(0.353)
Min Chi-Sq	yes	no	yes	no
MLE	no	yes	no	yes
observations	209	209	209	209

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

characteristics.

In the first specification, the first difference equation is a linearized Gompertz model, given by:

$$\log(pen_{it}) - \log(pen_{it-1}) = \alpha[\log(pen^*_{it}) - \log(pen_{it-1})]$$

The equilibrium penetration $\log(pen^*)$ as a linear function of demand determinants:

$$\log(pen^*_{it}) = \beta \log(X_{it})$$

X_{it} includes price, income, mobile phone penetration and other sociodemographic variables. The results of the estimation are given in Table 7. Price, income and sociodemographic characteristics have the expected signs. Decomposing the effect of cellular penetration in the different Circle types, we find confirmation of the main conclusions of the static models. The network effect appears more pronounced in low penetration Circles and some evidence of substitution is found for Circles of type A.

We now estimate the second diffusion process, which writes:

$$pen_{it} = \frac{pen^*_{it}}{1 + \exp(-a_{it} - b_{it}\, t)} \tag{2}$$

This model is more flexible and allows for nonconstant diffusion parameters. Diffusion follows a logistic process. a_{it} represents the location parameter: it shifts the diffusion function without affecting the S-shape. b_{it} is the speed of the diffusion process. We include all sociodemographic variables and the penetration of mobile

Table 7: Diffusion Equation 1: Linearized Gompertz Model

variable: $\log(pen_{it}) - \log(pen_{it-1})$	(1)	(2)	(3)	(4)	(5)
log(p)	-0.073^{**}	-0.067^{**}	-0.091^{**}	-0.082^{**}	-0.076^{**}
	(0.032)	(0.032)	(0.053)	(0.035)	(0.032)
log(y)	0.131^{***}	0.090^{***}	0.139^{***}	0.097^{***}	0.118^{***}
	(0.038)	(0.033)	(0.038)	(0.033)	(0.038)
log(liter)	0.118	0.095	0.121	0.108	0.132^{*}
	(0.081)	(0.068)	(0.084)	(0.071)	(0.080)
log(castes)	-0.042^{**}	-0.030^{***}	-0.044^{**}	-0.032^{*}	-0.039^{*}
	(0.020)	(0.017)	(0.020)	(0.017)	(0.019)
$\log(pen_{it-1})$	0.119^{***}	0.080^{***}	0.128^{***}	0.090^{***}	0.109^{***}
	(0.023)	(0.021)	(0.024)	(0.022)	(0.023)
log(cellpen)	0.017	-0.036^{*}	-	-	0.0003
	(0.020)	(0.027)			(0.0003)
log(cellpen)*circle-A	-	-	−0.001	-0.011^{**}	-0.032^{**}
			(0.004)	(0.004)	(0.012)
log(cellpen)*circle-B	-	-	0.004	−0.007	-
			(0.004)	(0.005)	
log(cellpen)*circle-C	-	-	0.003	−0.006	-
			(0.004)	(0.004)	
observations	171	171	171	171	171
time dummies	no	yes	no	yes	no

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 8: Diffusion Equation 2: Logistic Regression

variable: pen_{it}	(1)	(2)	(3)
pen*	0.162^{***}	0.184^{***}	0.182^{***}
	(0.015)	(0.025)	(0.025)
p	-0.0000005	-0.000004	-0.0000009
	(-0.000006)	(-0.000007)	(-0.000006)
y	0.00002^{***}	0.00002^{***}	0.00002^{***}
	(0.000003)	(0.000003)	(0.000003)
liter	0.0092^{***}	0.0086^{***}	0.0087^{***}
	(0.001)	(0.001)	(0.0010)
castes	0.0015	0.001	0.001^{*}
	(0.0007)	(0.007)	(0.0006)
cellpen	-0.010	-	0.010
	(0.009)		(0.007)
cellpen*circle-A	-	-0.018^{***}	-0.028^{***}
		(0.005)	(0.006)
cellpen*circle-B	-	0.009	-
		(0.09)	
cellpen*circle-C	-	0.073^{**}	-
		(0.036)	
observations	190	190	190

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

phones in the parameter b. In the location parameter a, we include fixed Circle effects (i.e. $a_{it} = a_i$), allowing location to depend on the circle types[16]. The model is estimated with nonlinear least squares, after adding an error term to Equation 2. The results are given in Table 8. All variables have the expected sign. As for the diffusion of mobile telephones, we still find a positive, though non significant network effect. In Column (2) the effect of mobile penetration is interacted with Circle dummies. The results confirm the analysis above: in A-Circles cellular penetration has a negative impact of mobiles on the speed of diffusion of fixed lines. In the other Circle types the estimated effect is positive.

The application of the two proposed diffusion models confirms the findings of the previous specifications. For low level of penetration, the network effect is more important and mobiles and fixed lines have a complementary development. In a more mature phase, consumers start substituting fixed with mobile services. There is no evidence that mobiles diffusion is displacing fixed lines in low penetration Circles.

5 Supply of telecommunications: investment

As mentioned in Section 1, universal service policies and the development of competition can both contribute to stimulate telecommunications diffusion. If the development of competition is able to induce an increase of investment in the sector, we can hope that autonomous market driven development would lead to higher telecommunications diffusion, making direct public intervention less crucial. To assess the impact of liberalization on the performance of the sector, we estimate a supply equation similar to the one proposed in Roller and Waverman

[16]Other specification has been tested, for instance including the NTP dummy in both a_{it} and b_{it}. The inclusion of the NTP dummy allows to see if the policy change created a 'jump' and/or an acceleration of the diffusion process. Both coefficient were not significant and the other estimates were not particularly affected.

(2001). The endogenous variable is the state level of investment. We estimate the following equation:

$$\log(inv_{it}) = \beta_0 + \beta_1 \log(area_i) + \beta_2 \log wl_{it} + \beta_3 \log(p_{it}) + \beta_4 X_{it}$$

Where $area$ is the geographic area of the State, wl is the waiting list (which aims to represent potential demand) and X are other control variables. In particular, we use as a control variable the number of competitors of the regulated firm in the basic services. In principle, notwithstanding the results discussed in the previous Sections, mobiles phones can also exert a competitive pressure on the fixed operators, altering profit opportunities. We thus also estimate the model including the number of mobile operators in the different Circles. This does not change the qualitative results not alter significatively the magnitude of the effects (results not shown). Data on investment (State-wise capital outlays) are published by the incumbent firms and not by competitors. The estimation gives nevertheless some interesting insights on the differences in the investment behavior in the different States/Circles (see Table 9). Consistent with the findings of previous studies, we find a positive impact of geographic area. Moreover, the regression shows a positive and significant impact of the waiting list wl: investment is demand responsive. We also find a positive and significant impact of competition. The coefficient of the price is very small and non significant, meaning that profitability would not have an impact on the investment decision. Also in this case, using the price as an explanatory variables probably introduces endogeneity problems. For these reason, we replace the average price with other profitability measures. As mentioned, Circle dummies capture some characteristics related to the profitability of the different Circle Types. We also add population density, which could affect the average main lines profitability. After adding these new controls, the competition variable turns out not to be significant. To disentangle the effect of competition from the profitability characteristics of the Circles, we build new variables interacting competition with the different circle categories. This identification strategy is of the same nature that the one used in assessing the impact of mobile telephone diffusion on the demand for fixed lines (Sections 2, 3, 4). We now estimate:

$$\log(inv) = \beta_0 + \beta_1 \log wl_{it} + \beta_2 \log(area_i) + \beta_3 \log(density_{it}) + \sum_j \beta_j comp * circle_j$$

Where circle$_j$, $j \in \{A, B, C\}$ are dummies for the circle classification. The results are given in Column 2. We see that competition has a positive impact on investment in type A and B Circles (which are the ones with higher expected profitability) but it is non significant in C-Circles (the low penetration ones).

We finally perform a similar regression using the equipped capacity as a measure of investment. Equipped capacity measures the total capacity of the switching exchanges, i.e. the maximal number of lines that can be connected. Data on capacity, published by the Department of Telecommunications, include the capacity provided by the private undertakings. They take into account private entry and, contrarily to capital outlays, do not refer only to the public incumbent. The results, presented in Table 10 are directly comparable to the ones in Table 9. All the significant coefficients, and in particular the one describing the impact of competition, have the same sign and similar magnitude. We also replace the left hand side variable ($capac$) with the excess capacity (i.e. the difference between the capacity installed by the firms and the active lines). The results are very similar in sign and magnitude (output not shown) and in this case the effect of competition in C-Circles is even negative (and still not significant).

Table 9: Investment Equation 1

variable: inv	(1)	(2)	(3)
p	0.031	-	-
	(0.276)		
wl	0.408^{***}	0.210^{***}	0.304^{***}
	(0.071)	(0.033)	(0.037)
area	0.341^{***}	0.546^{***}	0.659^{***}
	(0.078)	(0.038)	(0.043)
density	-	0.617^{***}	0.733^{***}
		(0.042)	(0.410)
comp	0.341^{***}	0.040	-
	(0.054)	(0.037)	
comp*circle-A	-	-	0.231^{***}
			(0.040)
comp*circle-B	-	-	0.085^{***}
			(0.055)
comp*circle-C	-	-	0.087
			(0.120)
circle-level fixed effects	no	yes	no
observations	115	133	133

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 10: Investment Equation 2

variable: capacity	(1)	(2)
wl	0.131^{***}	0.254^{***}
	(0.043)	(0.042)
area	0.471^{***}	0.583^{***}
	(0.029)	(0.043)
density	0.680^{***}	0.905^{***}
	(0.060)	(0.050)
comp	0.095	-
	(0.083)	
comp*circle-A	-	0.368^{***}
		(0.082)
comp*circle-B	-	0.267^{**}
		(0.116)
comp*circle-C	-	0.089
		(0.726)
time dummies	yes	yes
circle-level fixed effects	yes	no
observations	197	197

*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

The results seem to suggest that the existence of competition stimulates investment in more profitable areas, but not in regions with less developed markets/less demand potential. These findings do not support the idea that the protection of its monopoly position is at the origin of the low levels of investment of the incumbent. In low profitability ones entry does not seem to have a significative impact on investment. The benefits of competition are thus concentrated in the Circles with the highest expected profitability. The results goes more on the direction of suggesting the fact that market driven investment tends to concentrate in profitable areas, potentially increasing the gap in penetration between profitable and less profitable segments of the market. Public intervention would than be needed to stimulate investment in low penetration areas.

6 Conclusion

This paper analyzes the Indian telecommunications market for mainlines, trying to derive some preliminary evidence on the determinants of mainlines diffusion and the impact of the contemporaneous development of mobile telephony. The results suggest that (access) price elasticity for main lines might be larger than the usual estimates for developed countries, although decreasing with time and smaller in higher penetration zones. For this reason, subsidized access might be more effective than previously thought. Moreover, literacy rate and other sociodemographic variables seem to have a large impact on demand: they are important engines of telecommunications development. Considering the relationship between fixed and mobile telecommunications, we find that a positive network externality is present in low penetration areas. On the contrary, where the telecommunications market is more developed, we find evidence of displacement of fixed lines by mobile telephony. We interpret these results as suggestive that the network effect between mobiles and fixed phones is determinant at the first stages of telecommunications diffusion. In more mature markets, a substitution effect arises. The existence of substitution in most developed areas challenges the possibility of cross subsidization of less developed Circles with higher taxes/tariffs in the most developed ones. Although competition does not seem being currently reducing the revenues in high profitability areas, substitution between fixed and mobiles might undermine cross-subsidization policies. Where fixed and mobiles are substitutes, the development of a competitive mobile telephony market can also play a role in stimulating efficiency and price reductions, thus reducing the need for direct universal service policies. The last part of the paper provide some evidence that the introduction of competition in the fixed as well as in the mobile segments have boosted investment in the regions where the telecommunications market is more mature. However, in very low penetration areas, entry seems not to have a significant impact on investment. The concerns about the increasing gap between more and less developed regions are thereby reinforced by our results. For stimulating investment in less developed areas some direct intervention seems to be necessary: a true competition for the market and an efficient subsidization policy (public funds assigned through non discriminatory auctions) could be a response to this problem.

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