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Vergara, Sebastián and Grazzi, Matteo

ECLAC. United Nations

29 April 2011

Online at <https://mpra.ub.uni-muenchen.de/33266/>

MPRA Paper No. 33266, posted 09 Sep 2011 14:22 UTC

ICT Access in Latin America^φ

Evidence from Household Level

Matteo Grazzi
matteo.grazzi@cepal.org

Sebastián Vergara^θ
sebastian.vergara@cepal.org

Division of Production, Productivity and Management
Economic Commission for Latin America and the Caribbean (ECLAC)
United Nations

Abstract

The diffusion of Information and Communication Technologies (ICTs) is becoming a central policy issue for developing countries, being identified by international policy-makers and scholars as an important driver of knowledge, innovation and economic growth. We analyze ICT access patterns in seven Latin American countries. In particular, we study the socio-economic determinants of the presence of computers and Internet connection at household level. Descriptive data show that ICT diffusion is concentrated in narrowly defined segments of income and educational groups in each country. Across countries, there is also evidence that the lower is the ICT diffusion, the higher is the inequality of that diffusion. Econometrically, we model the probability that a household has or has not adopted computer technologies and Internet access. The results confirm that variables such as income, education and rural/urban areas are key determinants of ICT diffusion. Additionally, there is evidence of geographical network effects and complementarities between Internet uses at different locations.

JEL Classification: L63, O33, O54, C24

Keywords: ICT Access, Sample selection, Latin America.

^φ This paper was developed within the research activities of the Project “*Observatory for the Information Society in Latin American and the Caribbean (OSILAC), Third Phase*”. OSILAC III is a cooperating project between The International Development Research Centre (IDRC) and the Division of Production, Productivity and Management, ECLAC-UN (<http://www.eclac.cl/socinfo/osilac/>). The authors thank the statistical assistance of Cesar Cristancho and comments and suggestions from Barry Reilly and participants at the 6th European Meeting on Applied Evolutionary Economics held in Jena, Germany, May 23, 2009. Usual disclaimers apply.

^θ *On Leave*; currently at *The Economics of Innovative Change* Research Program, Friedrich-Schiller University and Max Planck Institute of Economics, Germany.

I. Introduction

It is widely recognized that the diffusion of Information and Communication Technologies (ICTs) is an important engine of economic development. In particular, high levels of ICT diffusion in homes bring benefits to a country in terms of improving the quality of available human capital, increasing demand for technological goods and contributing to the democratization of political structures by providing a greater range of people with a better access to information. Moreover, at micro level, families using ICTs gain several advantages, such as obtaining a better access to information and knowledge, improving communication efficiency, and gaining technological skills which are increasingly important in the job-market. Having access to a home computer, for instance, increases the probability of starting a new business (Fairlie, 2006), connecting ICT diffusion with some emerging issues of business analysis, such as entrepreneurship. Furthermore, especially in rural areas, households are often not only consumers but also productive units, whose productivity can be strongly enhanced by ICTs. Then, ICT diffusion can also play a major role in poverty reduction, through better diffusion of information, more effective promotion of social programs and improved governance and political participation.¹

The concept of *digital divide*² has then become a relevant public issue, receiving increasing attention both at domestic and international level, taking different dimensions. Indeed, researchers in developed countries –where ICT penetration is higher – have shifted their attention from the traditional distinction between *haves* and *have-nots* to the new concept of “digital inequality”. It refers not only to mere differences in access, but also to different ICT usage patterns (DiMaggio and Hargittai, 2001). On the contrary, in developing countries, where ICT diffusion is still at earlier stages, access availability remains an important open issue.

In this perspective, research on drivers of technology diffusion in households is crucial in order to define the appropriate policies to address the *digital divide* in developing countries. Nevertheless, the existing empirical literature is mostly based on the experience of developed countries, while it is still missing a comprehensive analysis founded on data at household or individual level from the developing world.³ This paper contributes to fill this gap, evaluating the main socio-economic determinants of the presence of computer and Internet connection at

¹ For a literature review on ICT and poverty, see Adeya (2002).

² In the early years of ICT diffusion, the digital divide was defined as “*the gap between individuals, households, business and geographic areas at different socio-economic levels with regard both to their opportunities to access ICTs and to their use of the Internet for a wide variety of activities*” (OECD, 2001). More recently, the definition of digital divide has evolved and it is including the quality of access dimension. For example, the ITU define it as “*the gap between those who benefit from digital technology and those who do not*” (ITU, 2005).

³ For a cross-country analysis on ICT penetration determinants in developing countries, see Chinn and Fairlie (2006).

household level in seven Latin American countries. Using data from *National Household Surveys*, we model the probability that a household has or has not adopted computer and Internet technologies. In addition to the traditional determinants found in the empirical literature, such as income, education, we also explore the role played by other factors commonly identified in theoretical discussions but not sufficiently investigated in the empirical literature. In particular, we analyze the role played by geographical network effects, presence of students in the households and complementarities between Internet usage at work and at home.

The paper is organized as follows. In Section II is presented a review of the empirical literature concerning ICT access in households. Section III illustrates the overall patterns of ICT diffusion in Latin America. Then, Section IV builds up an economic and econometric framework to develop the analysis at household level, and Section V discusses the estimation results. Finally, Section VI concludes and indicates some future research areas.

II. What Do We Know About ICT Access at Household Level?

The existing economic literature on ICT penetration in households is still in its early stages. It basically consists of descriptive studies that highlight the correlation of access to technologies – computer adoption, Internet access, type of Internet connection - with household or individual socioeconomic characteristics such as income, education, ethnicity, region and age (e.g. Kominski and Newburger, 1999; OSILAC, 2007). The analysis of the digital divide at different socio-economic dimensions is the central issue of the ICT literature at household level (Dewan and Riggins, 2005). In fact, regardless of the definition adopted, the strong policy implications of the digital divide has encouraged several institutions and scholars to analyze the phenomenon.

For instance, the National Telecommunication and Information Administration (NTIA) has pointed out the correlation between education, income, race and age and ICT access in the US (NTIA, 2002, 2000, 1999, Leigh and Atkinson, 2001). Indeed, NTIA (2002) establish that Internet is positively correlated with income, education and employment status. Additionally, young individuals are more likely to have ICT access; there is no evidence of a gender gap, while there are important ICT gaps among Whites, Asian Americans, Blacks and Hispanics. Likewise, Chaudhuri *et al.* (2005) used data from two original surveys of US households to analyze the socio-economic factors that affect Internet adoption. Despite the relevance of income and education, the results suggest that student condition is a significant determinant, while African Americans and Hispanics are found to be less likely to be online than other ethnic categories.

Based on Chaudhuri *et al.* (2005), Flamm and Chaudhuri (2007) developed an ordered decision structure taking into account that broadband service itself may not be available in all areas. The analysis suggests that price is a significant driver of the broadband demand. Furthermore, controlling for price, the authors show that other non-price factors also seem to affect dialup and broadband demand rather differently. For instance, the effect of marital and student status, gender and metropolitan location, over the choice of low and high speed service is not homogeneous. They find clear differences among households located in urban, sub-urban and rural areas over the broadband choice. Also following Chaudhuri *et al.* (2005), Fairlie (2003 and 2004) investigated the causes of racial differences in rates of computer and Internet use in the U.S. The results show that racial differences in income, education and occupation explain an important part –but not all– of the gap between whites and other ethnicities. While no evidence has been found for price or school differences, language barriers could justify the remaining part of the gap. Ono and Zavodny (2007a) confirm the results obtained by Fairlie, analyzing the differences in ICT access and use between immigrants and natives in the U.S. They show that immigrants are less likely to have access to computers and Internet at home and that English ability plays an important role in this gap⁴. Other studies with reference to the racial digital divide are Hoffman, *et al.* (1997) and Hoffman and Novak (1998).

A number of recent studies have focused on the identification of other possible determinants of computer and Internet penetration. For example, Goolsbee and Klenow (2002) investigated the role of geographic network effects in the diffusion of home computers. They found that people in the U.S. are more likely to own computers in areas where there is a higher computer concentration. Moreover, several contributions in the literature also recognize the role played by psychological factors and attitudes towards the adoption of new technologies. Demoussis and Giannakopoulos (2006a) for instance estimated a dynamic random effects Probit model to analyze the household characteristics which influence the probability of computer ownership in Greece. The panel nature of the data (1997-2001) allowed them to verify the existence of serial persistence, which could be caused by genuine state dependence and by unobserved heterogeneity of the households. In particular, they found that the latter accounts for almost a third of the variance of their model. It seems that an important part of the unobserved heterogeneity could be explained by the different attitude of households towards technology. Robertson *et al.* (2007) estimate a Probit model of residential computer adoption in the U.K.

⁴ In another study, Ono and Zavodny (2002) examine the gender gap on ICT usage. Using data from 1997 to 2001, the results show not only women were significantly less likely than men to use Internet in the mid-1990s, but also that the gap disappears by 2000. However, women continue to be less frequent and less intense Internet users than men.

including a proxy variable measuring psychological attitudes towards technology⁵. The results show that this variable is significant and it also improves forecasting outcomes when compared to the analogue standard Probit.

With the objective of decoupling access and usage analysis, Goldfarb and Prince (2008) analyze separately ICT access and usage in the US. Interestingly, they found that while income and education are positively correlated with adoption, they are negative correlated with hours spent online. The authors argued that the most likely explanation for this is that low income individuals spend more time online because of their lower opportunity cost. The pricing structure of Internet –fixed connection and near-zero usage fees- are particularly important to explain this.

In an appealing international comparison, Ono and Zavodny (2007b) examine the extent and causes of digital inequality using microdata from US, Sweden, Japan, Korea and Singapore⁶. The study examines patterns and determinants of computer and Internet access and use, focusing in cross-country differences across education, income, age, and sex groups. Overall, the results are consistent with the hypothesis that the digital divide reflects pre-existing social and economic inequalities. Though, the results show no systematic relationship between pre-existing inequalities and differences in computer ownership. The authors interpret this by considering that computers diffusion has yet reached a critical mass in these countries. But demographic and socioeconomic characteristics are still related to whether an individual uses both a computer and Internet, even when access is granted. Remarkably, access to a computer may ameliorate but does not necessarily erase all digital divides.

The European Union (EU) has also been subject of several studies concerning ICT diffusion. Vicente and Lopez (2006) analyzed determinants of ICT adoption at both country and individual level. Beyond the importance of income over both computer and Internet access, their results also confirm the relevance of university education. Moreover, Internet adoption seems to be only modestly sensitive to price. In another EU analysis, Demoussis and Giannakopoulos (2006b) use a cross-sectional dataset for 14 EU member states to estimate an ordered Probit model with selection bias. The empirical results confirm that Internet access is driven by household income, family size, education, age, gender, location (urban-rural) and cost of Internet access. Additionally, Internet usage is positively influenced by household income, education and

⁵ This is implemented by using the Technology Acceptance Model (TAM) variable among the independent variables. Robertson *et al.* (2007) applies the representation of the TAM model by summarizing three TAM perceptions: ease of use, usefulness and enjoyment into a single variable defined as ICT utility.

⁶ Chan (2006) analyze the digital divide in Taiwan by using a pseudo panel dataset and estimating ICT penetration rate regressions with the Generalized Method of Moments (GMM). The results confirm that income and human capital are crucial in explaining the digital divide in PCs, Cable TV and cellular phones, but curiously Internet is an exception.

individual actions for skill acquisition and learning development. The authors also analyze the ICT diffusion by sampling the data in north and south countries, and the evidence shows that a geographical digital divide is present in the EU. Interestingly, the decomposition analysis reveals that the differences in access for the two groups of countries are not related to differences in observed determinants. Indeed, the geographical divide is due to unobservables, like cultural and attitudinal differences towards new technologies. Thus, the policy implication is remarkable: uniform policies across the EU will not be effective to reduce the observing digital divide.

In a regional perspective, Peres and Hilbert (2009) provide insightful information about ICT diffusion in Latin America. Among other issues, they focus on different dimensions of the digital divide with the developed world. Interestingly, such a gap is declining in the mobile technologies, while it is increasing in terms of computer, internet and broadband access.⁷ Gutierrez and Gamboa (2008) focuses on the digital divide among low income people in Colombia, Mexico and Peru. Their results show that education is the most important factor limiting ICT diffusion. Additionally, the authors establish the presence of a digital gender gap in Peru, but not in Mexico and Colombia. In a specific analysis of the Mexican case, Mariscal (2005) shows both the existence of high inequality of the ICT, and that the digital divide is not narrowing. Furthermore, the paper discussed the social capital concept as a key aspect in the design and implementation of a universal access policy.

A different strand of the literature deals with theoretical considerations of the ICT diffusion. Greenstein and Prince (2005) for example analyze the geographic diffusion of the Internet in the US for both households and firms. Developed into the framework of an economic diffusion theory, the authors conclude that the Internet diffused temporarily – because of the lack of maturity - to several urban areas with their complementary resources. Once the applications matured, the leader areas lost their position and ISP technologies diffused widely after commercialization. In an international framework, Venkatesch and Shih (2005) investigated how different diffusion theories –evolutionary, leapfrogging, structural and agentic - match the empirical ICT diffusion in the US, Sweden and India, in order to obtain a better understanding of how technology is integrated into households. They found that no particular theory can exclusively explain all developments, and all four theories apply with different degrees. The authors argue that the determinants by which the computers are integrated into households are similar across cultures, stressing the role of impact and utilitarian outcomes as major determinants

⁷ Additionally, the work by Peres and Hilbert (2009) contains several articles analyzing the digital convergence, ICT industries, regulation, intellectual property rights and other ICT topics in Latin America.

of the level of technology usage at home. The results also confirm the strong correlation among the use of computer and other technologies⁸.

Overall, the literature on ICT diffusion based on micro-data at individual and household level is still limited, and it is particularly weak in developing countries. However, the increasing availability of datasets concerning technology diffusion and use is encouraging the development of a better understanding of ICT diffusion at both empirical and theoretical levels. The significant implications of ICTs over economic, social and cultural dimensions deserve a more precise knowledge on its opportunities, problems and challenges.

III. Main Patterns of ICT Access in Latin America

The ICT penetration in Latin America and the Caribbean is significantly below the developed world access for computer and Internet (See Figure 1). While the number of computers, Internet and broadband subscribers in the developed countries are respectively 62, 24 and 19 per 100 individuals, in Latin America and the Caribbean all these indicators are below 12 per 100 individuals. And, as discussed by Peres and Hilbert (2009), such a gap is not narrowing in these dimensions. Figure 1 also shows that ICT access in the region is slightly higher than in the developing world and it is much greater than in the less developed countries. However, while the diffusion of computers in the region is clearly higher, the access to Internet and broadband is basically similar among Latin America and the developing world.⁹

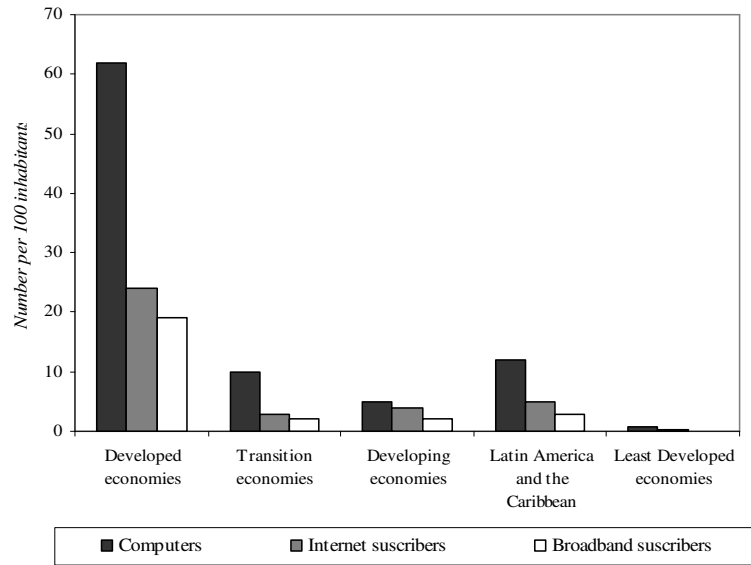
The region itself reflects deeply different patterns of diffusion, both between and within countries. Sub-regionally, South America shows higher levels of penetration than Central America and the Caribbean. For example, considering the ITU's ICT Development Index (IDI)¹⁰, Argentina, Chile and Uruguay are the better ranked Latin American countries in 2007 (ranking 47, 48 and 49 respectively), while Haiti is by far the worst ranked (136th, after Mauritania and Benin) (ITU, 2008).

⁸ This result is important for technology design issues. A better understanding of how actual technologies are used and how can interact with future applications can lead to significant changes in ICT diffusion across households.

⁹ However, these data should be taken with caution, as the comparison is made by using the average of all developing countries. For example, Latin American countries have a disadvantage situation in ICT access in comparison with East Asian countries (ITU, 2008).

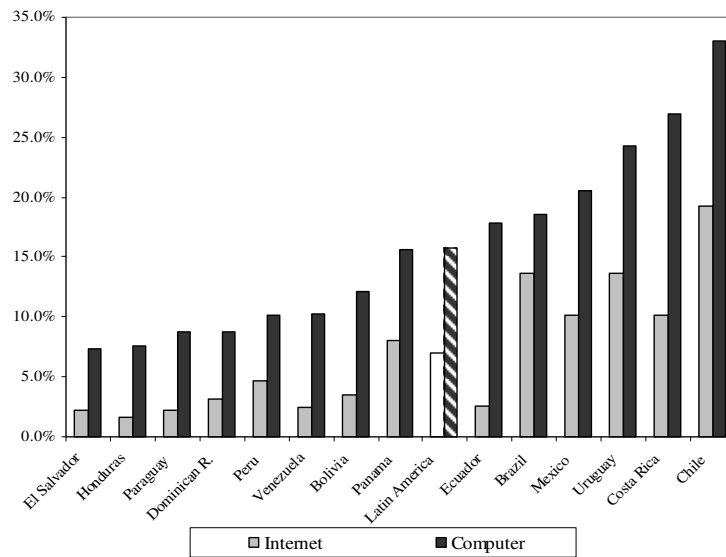
¹⁰ The ITU's ICT Development Index (IDI) compares ICT developments in 154 countries over a five-year period from 2002 to 2007. It is created by combining 11 indicators related to ICT access, use and skills into a single measure.

Figure 1
ICT Diffusion across regions in the world
(Percentages)



Source: International Communication Union (ITU) (2008), *Statistics Bulletin*, www.itu.com.

Figure 2
Latin America: ICT Household Access^a
(Percentages)



Source: authors' elaboration based on the OSILAC ICT Statistical Information System, <http://www.cepal.org/tic/flash/>

^a Data corresponding to latest available year. The average for Latin America corresponds to the average of the displayed countries.

Focusing on the access issue, Figure 2 presents data on computer and Internet penetration at household level for 14 Latin American countries. On average, the penetration rates for computer and Internet for Latin America at household level are 15% and 7%, respectively. Clearly, there is an important heterogeneity in the ICT diffusion across countries. While Chile, Costa Rica, Mexico and Brazil show relatively high penetration rates; Honduras, El Salvador and Paraguay are the most ICT delayed countries. Overall, countries with higher computer adoption rates tend to have higher Internet access rates, but there are also some special cases. Costa Rica, for example, not only has a relatively high level of computer adoption, but also a large gap between computer and Internet adoption rates¹¹. On the contrary, Brazil presents the lowest gap among computer and internet adoption: the difference between computer and Internet penetration rates is just 4.9%.

Figure 3 shows ICT penetration rates by per capita income quintiles for the seven Latin American countries analyzed. Not surprisingly, higher income quintiles are associated with higher ICT penetration rates. For example, in the Chilean case the penetration rates in Chile for computer and Internet adoption in the fifth quintile are 59% and 42%, and in Costa Rica these participations are 55% and 30%, respectively. Furthermore, differences in ICT penetration are not homogeneous along subsequent quintiles, and the fifth income quintile concentrates the bulk of ICT penetration. For instance, in Honduras, the computer adoption rate rises from 0.6% in the first income quintile to 8.7% in the fourth, and then it jumps strongly to 26% in the fifth quintile. Such discontinuity is more evident in countries with limited ICT diffusion, such as El Salvador, Honduras and Paraguay. In countries with higher rates of technology diffusion - namely Brazil, Chile, Mexico and Costa Rica - the concentration of ICT diffusion in the fifth income quintile is relatively lower.

Likewise, the distribution of ICTs across educational quintiles follows a similar pattern: higher educational quintiles have higher access to both computer and Internet (see Figure 4). For example in Mexico, the computer and Internet adoption rates in the first quintile are 1.3% and 0.2%, respectively; while the penetration rates in the fifth quintile are 60.3% and 34.5%, respectively. In the case of El Salvador, it is particularly clear the non homogeneity in the ICT diffusion. In fact, the increasing ICT diffusion for subsequent educational quintiles is relatively homogeneous from the first until the fourth quintile, but it increases more than proportionally in

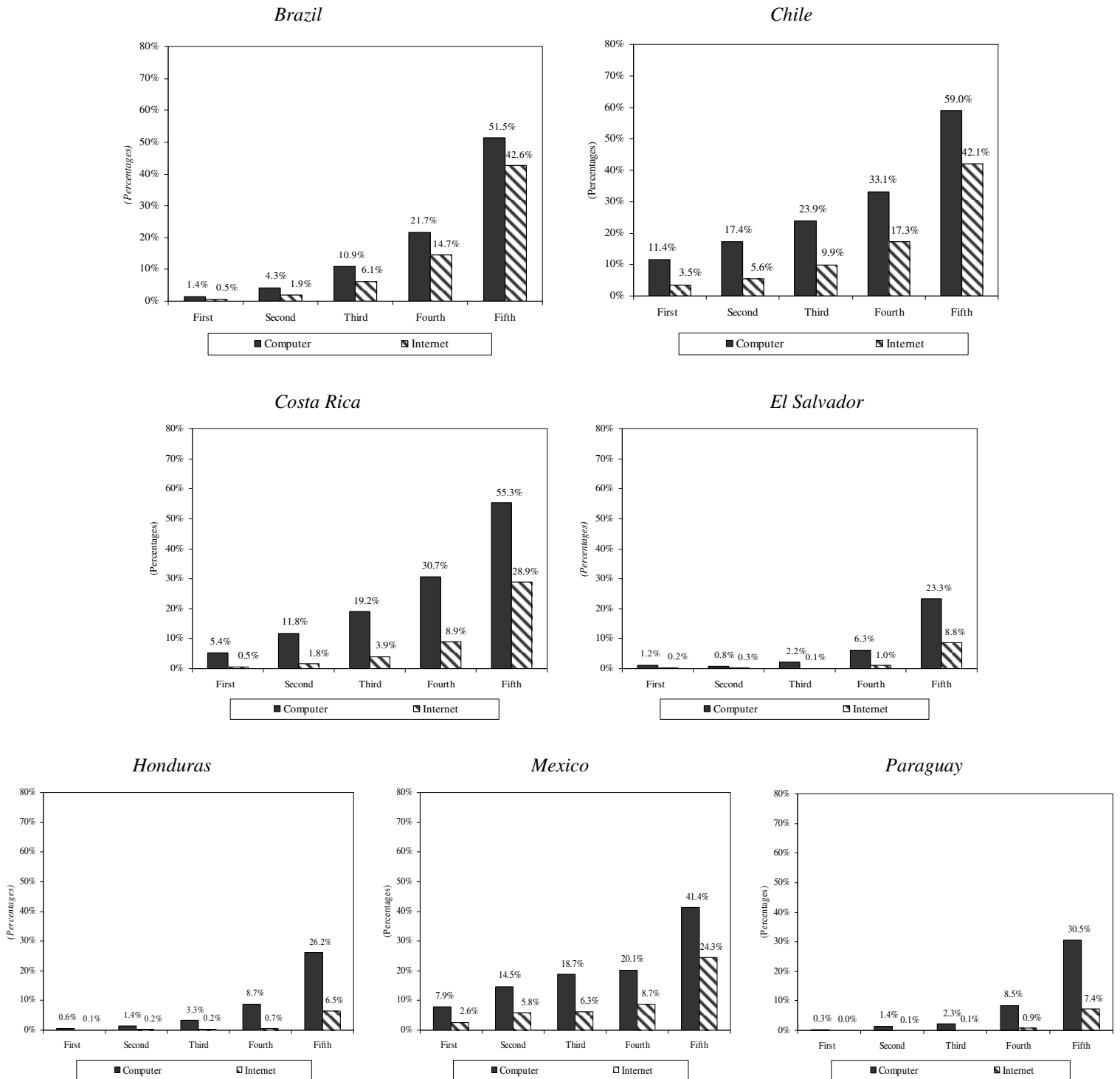
¹¹ Ecuador also evidences a striking situation: while it shows a relatively high computer adoption rates (18%) –higher than Latin American average-, it also evidences a very low Internet access rate (2.5%).

the fifth quintile. In fact, while the computer adoption rate rises from 0.2% in the first educational quintile to 4.0% in the fourth, it arrives to a peak of 26% in the fifth quintile.

Table 1 presents the computer and Internet penetration rates disaggregated by urban and rural areas for the period 2000-2006, subject to data availability in each country. Three messages emerge from the data. First, all countries evidence a growing pattern in both the computer and Internet penetration rates, but the level and speed of the technology diffusion is certainly heterogeneous. On one extreme, Chile's computer adoption rate has increased from 17% in 2000 to 33% in 2006, and the Internet access rate has grown from 8% to 19%. On the other extreme, Paraguay's computer adoption rate has raised from 5% in 2001 to 9% in 2005, and the Internet access rate from 1% to 2%. Second, the ICT diffusion is not uniform throughout different geographic locations within each country. Indeed, there is a clear digital divide between rural and urban areas. For instance, even in Costa Rica, the country with the lowest urban-rural gap, while the urban computer and internet penetration rates are 35% and 14% respectively (latest available year), the rural access rates are 14% and 4%. As a result, the computer penetration rate in rural areas is 39% of the penetration rate in urban areas; and this participation decreases to only 26% in the case of Internet access. Third, although the digital divide among rural and urban areas is narrowing across time, this reduction is slow. In Chile, while the Internet penetration rate was 9.6% in the urban areas and 0.8% in the rural areas in 2000, five years later these figures were 21.6% and 2.8% (see Table 1). Therefore, the ratio of rural/urban penetration rates increased from 8% to 13%.

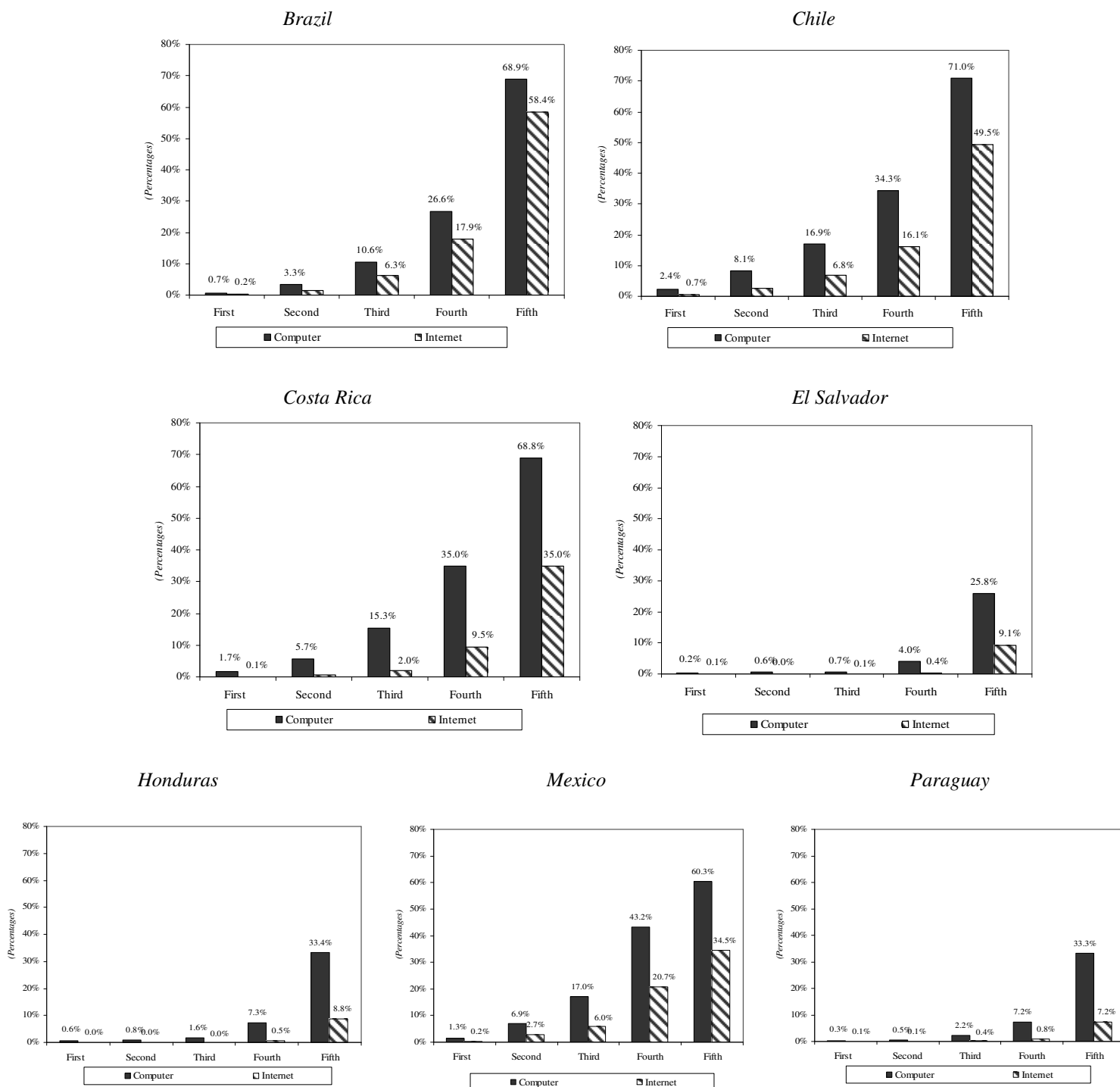
The overall picture of ICT access in Latin America shows that computer and Internet diffusion is still low compared with developed countries. Additionally, it is greatly concentrated in few segments of the population, namely the highest income and educational quintiles. This fact, together with the extensive gap between rural and urban areas, provides evidence with respect to the non-homogeneity of the ICT diffusion process in the region, which seems to reflect pre-existing inequalities in other socio-economic characteristics. This facts about ICT diffusion in Latin American are also consistent with empirical evidence in developed countries (NTIA, *various issues*; Vicente and Lopez, 2006).

Figure 3
Latin America: ICT Access by income quintiles
(Percentages)



Source: authors' elaboration based on the OSILAC ICT Statistical Information System, <http://www.cepal.org/tic/flash/>, latest available year.

Figure 4
Latin America: ICT Access by education quintiles^a
(Percentages)



Source: authors' elaboration based on the OSILAC ICT Statistical Information System, <http://www.cepal.org/tic/flash/>, latest available year. ^a Correspond to quintiles of the average education years of adults in the household.

Table 1
Household access to computer and Internet
(Percentages)

<i>Country</i>	<i>Access/Year</i>	2000	2001	2002	2003	2004	2005	2006
Brazil	Computer	.	12.6	14.2	15.3	16.3	18.5	.
	<i>Urban</i>	.	14.6	16.3	17.5	18.9	21.4	.
	<i>Rural</i>	.	1.2	1.6	1.8	2.1	2.7	.
	Internet	.	8.5	10.3	11.4	12.2	13.6	.
	<i>Urban</i>	.	9.9	12.0	13.2	14.3	15.9	.
	<i>Rural</i>	.	0.5	0.5	0.7	0.8	1.1	.
Chile	Computer	17.5	.	.	24.9	.	.	33.1
	<i>Urban</i>	19.9	.	.	28.0	.	.	36.6
	<i>Rural</i>	2.2	.	.	4.7	.	.	9.9
	Internet	8.4	.	.	12.6	.	.	19.2
	<i>Urban</i>	9.6	.	.	14.3	.	.	21.6
	<i>Rural</i>	0.8	.	.	1.3	.	.	2.8
Costa Rica	Computer	13.7	17.3	19.9	.	23.7	26.6	.
	<i>Urban</i>	19.3	23.7	27.3	.	31.4	35.2	.
	<i>Rural</i>	5.3	7.5	8.7	.	12.0	13.7	.
	Internet	4.0	5.3	7.2	.	.	10.0	.
	<i>Urban</i>	6.0	7.8	10.5	.	.	14.3	.
	<i>Rural</i>	1.0	1.6	2.3	.	.	3.7	.
El Salvador	Computer	2.7	4.5	5.2	5.5	6.0	.	7.6
	<i>Urban</i>	4.3	7.1	8.1	8.5	9.1	.	11.4
	<i>Rural</i>	0.1	0.2	0.3	0.5	0.8	.	1.0
	Internet	1.0	1.6	2.3	2.4	2.0	.	2.4
	<i>Urban</i>	1.7	2.5	3.6	3.8	3.1	.	3.7
	<i>Rural</i>	0.0	0.0	0.0	0.1	0.1	.	0.1
Honduras	Computer	.	.	.	5.2	5.4	6.3	7.6
	<i>Urban</i>	.	.	.	10.1	10.6	11.7	14.1
	<i>Rural</i>	.	.	.	0.5	0.4	1.0	1.4
	Internet	1.4	1.5	1.4
	<i>Urban</i>	2.8	2.9	2.8
	<i>Rural</i>	0.1	0.2	0.1
Mexico	Computer	18.0	18.6	20.6
	<i>Urban</i>	30.3
	<i>Rural</i>	13.2
	Internet	8.7	8.9	10.1
	<i>Urban</i>	15.7
	<i>Rural</i>	5.7
Paraguay	Computer	.	5.2	5.4	6.2	6.4	8.7	.
	<i>Urban</i>	.	8.9	8.4	10.0	10.0	13.2	.
	<i>Rural</i>	.	0.5	0.8	0.9	1.2	1.7	.
	Internet	.	1.0	1.2	1.8	1.0	1.7	.
	<i>Urban</i>	.	1.7	2	3.1	1.7	2.7	.
	<i>Rural</i>	.	0.1	0.0	0.0	0.1	0.1	.

Source: OSILAC ICT Statistical Information System, <http://www.cepal.org/tic/flash/>.

IV. Methodology and Empirical Approach

a) Methodology

In this section we describe the economic model and the econometric approach used to analyze the determinants of ICT diffusion at household level in the Latin American countries selected. Following Fairlie (2004) and Vicente and Lopez (2006), a linear random utility function is employed to model the household's decision to have or to have not a computer at home. The utility associated with each of the two situations is assumed to be a linear function of a set of household's socio-economic characteristics (X_i), and of a stochastic term which represents unobservables and measurement errors (ε_i). Hence, the indirect utility of household i associated with having a computer ($U_{i,H}$) and not having it ($U_{i,N}$) can be expressed as:

$$U_{i,H} = X_i \beta_H + \varepsilon_{i,H} \quad (1)$$

$$U_{i,N} = X_i \beta_N + \varepsilon_{i,N} \quad (2)$$

Thus, household i will choose to have a computer if the utility associated with it is higher than the utility associated with not having: $U_{i,H} > U_{i,N}$. If we define a variable Y so that $Y_{i,H} = 1$ if the i th household owns a computer and $Y_i = 0$ if it does not, the probability that the i th household has access to a computer is $\Pr(Y_{i,H} = 1) = \Pr(U_{i,H} > U_{i,N}) = \Phi[X_i(\beta_H - \beta_N)]$, where Φ is the cumulative distribution function of $[\varepsilon_{i,H} - \varepsilon_{i,N}]$. Normalizing the utility of having no computer at home to zero ($U_{i,N} = 0$), we derive the empirical equation for computer adoption:

$$\Pr(Y_{i,H} = 1) = \Pr(U_{i,H} > 0) = \Phi[X_i \beta] \quad (3)$$

In a similar way, we can derive an equation to model the probability of household j to have an available Internet access at home:

$$\Pr(Y_{j,C} = 1) = \Pr(U_{j,C} > 0) = \Phi[X_j \theta] \quad (4)$$

where $U_{j,C}$ is the indirect utility associated with being connected to the Internet. Therefore, we can empirically analyze household determinants of computer adoption and Internet access through the estimation of β and θ parameters in the empirical equations (3) and (4). A common econometric

approach to estimate these equations by Maximum Likelihood Estimation (MLE) is the Probit model.¹²

The Probit model assumes that the error term is normally distributed with mean 0 and variance σ equal to 1, and $\Phi(\cdot)$ corresponds to the cumulative distribution function for a standard normal random variable. Nonetheless, a possible problem with this approach is that it does not consider the correlation between household choices regarding both computers and Internet. On the one hand, computer adoption is a prerequisite to having an available Internet connection at home. On the other hand, the decision of owning a computer can be founded on the fact that it is a necessary previous step to Internet connection. The key point is that a computer can be either a final good itself or just a requirement to have access to the web, depending on the characteristics of computer use in the household.

The linkage between these decisions raises an important econometric consideration. In fact, maximum likelihood estimation of two correlated Probit models seems to be a not fully efficient econometric procedure choice, as it ignores the correlation between the error terms. A natural extension of Probit estimation that takes into account such a correlation is the Bivariate Probit model (Biprobit) (Greene, 2003). In this model, the error terms follow a bivariate normal distribution:

$$\Pr (Y_{i,H} = 1) = \Phi [X_i \beta] \tag{5}$$

$$\Pr (Y_{j,C} = 1) = \Phi [X_j \theta] \tag{6}$$

$$E(\varepsilon_{i,H}) = E(\varepsilon_{j,C}) = 0 ; V(\varepsilon_{i,H}) = V(\varepsilon_{j,C}) = 1 ; \text{Cov} (\varepsilon_{i,H}, \varepsilon_{j,C}) = \rho \tag{7}$$

The Biprobit model is estimated by Full-Information Likelihood (FIML) procedures, using a likelihood function specified in terms of a standard normal bivariate probability function. The correlation between the two equations provides a more coherent framework to model both household decisions. However, given the nature of the data, the Biprobit methodology does not consider fully the character of the correlation (selection) between the variables in our empirical case. In fact, computer adoption determines completely the possibility of Internet connection, selecting households that can actually adopt it, and a non-random sample selection generates biased estimates (Heckman, 1979).¹³

¹² Some scholars use Logit estimations, assuming an error term logistically distributed (Vicente and Lopez, 2006). We prefer to use Probit models because of its theoretical extensions associated to the Bivariate Probit methodologies.

¹³ Also household decision about telephone fixed line access can be seen as correlated with Internet connection. In this case, the three household decisions can be modeled by using a Multivariate Probit analysis. However, this procedure is empirically complicated because the evaluation of the likelihood function requires the computation of trivariate normal integrals (Capellari and Jenkins, 2003).

An econometric approach that can be considered to deal with this problem is to specify a Bivariate Probit with sample selection model, and adapt the Heckman two-step procedure to this dichotomous case (Van de Ven, *et al.*, 1981). Intuitively, the Heckman procedure deals with sample selection as a specification problem. Hence, it attempts to solve it by inserting a proxy variable that captures the omitted part of the sample truncated mean that is attributable to selection. The Bivariate Probit with sample selection model (*Heckprobit*) is specified as follows:

$$\Pr (Y_{j,C} = 1) = \Phi [X_j\theta + \phi\lambda_i] \quad (8)$$

Where λ correspond to the inverse Mill's ratio (*Heckman correction term*). In this equation, the dependent variable is observed if $U_{i,H} = X_i \beta_H + \varepsilon_{i,H} > 0$. Thus, the computer adoption equation is specified as a selection equation. Empirically, the procedure follows the next steps. First, the selection equation is estimated by maximum likelihood. Then, this estimation is used to construct the inverse Mill's ratio ($\lambda = \phi(X'_i\theta) / \Phi(X'_i\theta)$) by using the pseudo residuals. These pseudo residuals represent the unobserved factors that determine household decision on having computer access. Finally, the selection correction term λ is included in the Probit equation, which is also estimated by maximum likelihood.

b) Empirical Approach

The data used in the econometric section come from the National Household Surveys conducted in seven Latin American Countries in 2005 and 2006. All the surveys are representative at national level and cover a wide range of socio-economic variables at individual and household level, such as income, education, age, occupation, household characteristics and location, among others. Additionally, the surveys include questions concerning computer adoption and Internet access (See Table 2).

Considering the methodological issues presented in the previous section, our empirical approach for the analysis of ICT determinants in each country is based on the following two equations:

$$\Pr (Computer=1) = \Phi (\alpha + \beta_0*Income_i + \beta_1*Education_i + \beta_2*Users_i + \beta_3*Rural_i + \beta_4*Work_i + \beta_5*Students_i + \beta_6*Network_{i,C}) \quad (9)$$

$$\Pr (Internet=1) = \Phi (\alpha + \beta_0*Income_i + \beta_1*Education_i + \beta_2*Users_i + \beta_3*Rural_i + \beta_4*Work_i + \beta_5*Students_i + \beta_6*Network_{i,I}) \quad (10)$$

Where *Income* corresponds to the per capita equivalent income of the household¹⁴, *Education* is the household education level measured by the average level of educational years of adults (age ≥ 18)¹⁵ and *Users* is the number of individuals potentially capable to use computers in the household (age ≥ 6). These variables are expected to be the most relevant socio-economic and demographic determinants of ICT diffusion. Income has been identified in the literature as a key factor in explaining technology adoption, operating on the household budget constraint (Vicente and Lopez, 2006). It is supposed to be particularly important in developing countries, where technology diffusion is still in an early stage and prices are relatively high. Also education should be an important driver of adoption, as it is necessary to be somehow technologically-skilled in order to use proficiently computers and the Internet. Finally, the larger the number of potential users in the household, the higher should be the household's utility of adoption.

Students variable correspond to the proportion of students in the household, which is supposed to influence positively the probability of having a computer and Internet connection. In fact, students usually have more advanced technological skills and may constitute an important engine of technologies adoption. *Rural* controls for the area (urban or rural) where the household is located. *Work* represents the use of Internet at work of at least one individual in the household and tests for complementarities between ICT use at work and at home.¹⁶

Finally, the *Network_{C,I}* variables correspond to the computer or Internet penetration rate in the geographical area where the household is located. These variables test for the existence of network effects respectively for computer and Internet diffusion. The hypothesis here is the existence of local positive spillovers of existing computer owners and Internet subscribers on households considering technology adoption, *i.e.* that households located in more digitally advanced regions have reduced costs or increased benefits in having a computer or Internet access. Costs of adoption may be reduced because of the possibility to learn about the technology from some friend or neighbour, while additional benefits could derive from the possibility to share software and to communicate with a larger number of people (Goolsbee and Klenow, 2002). The existence of network effect is tested at a specific geographical level for each country due to different data availability: we have calculated penetration rates by Federative Unit in

¹⁴ In order to take into account economies of scale in household consumption and obtain more precise income elasticity, we use an equivalent income measure, which is the total household income divided by the so-called LIS (Luxembourg Income Studies) equivalence scale. It is defined as the square root of the number of household members (Atkinson *et al.*, 1995).

¹⁵ The household education level is represented by an index representing the average educational attainment of adults (age ≥ 18). The exception is Mexico because of the lack of information concerning educational years of individuals.

¹⁶ See Annex 1 for a statistics overview of variables.

Brazil and Mexico, by Province in Chile, by Planning Region in Costa Rica and by Department in El Salvador, Honduras and Paraguay.

An important contribution of this paper is the fact that all the independent variables concern the household as a whole. On the contrary, most of the previous literature included in the regressions also variables referred to household head characteristics (*e.g.* Singh, 2004). This approach implicitly assumes that the decisions about computer and Internet adoption are taken by the household head. But this is a weak argument, especially in developing countries, where households are larger and a higher number of income earners can belong to the same household. Then, we argue that decision-making is a more complex process and that it is preferable to model the decision of ICT access on the characteristics of the entire household, considering it as a single unit.

Table 2
Household Surveys Description

<i>Country</i>	<i>Year</i>	<i>Survey</i>	<i>Institution</i>	<i>Households</i>
Brazil	2005	Pesquisa Nacional por Amostra de Domicílios (PNAD)	Fundacao Instituto Brasileiro de Geografia e Estatística (IBGE)	116,452
Chile	2006	Encuesta de Caracterización Socioeconómica Nacional (CASEN)	Ministerio de Planificación Nacional (MIDEPLAN)	73,720
Costa Rica	2005	Encuesta de Hogares de propósitos múltiples (EHPM)	Instituto Nacional de Estadística y Censos (INEC)	11,549
El Salvador	2005	Encuesta de Hogares de Propósitos Múltiples. (EHPM)	Dirección General de Estadística y Censos (DIGESTYC)	16,343
Honduras	2006	Encuesta Permanente de Hogares de Propósitos Múltiples (EPHPM)	Instituto Nacional de Estadística (INE)	20,581
Mexico	2006	Encuesta Nacional sobre Disponibilidad y Uso de las Tecnologías de la Información en los Hogares (ENDUTIH)	Instituto Nacional de Estadística y Geografía (INEGI)	4,813
Paraguay	2005	Encuesta Permanente de Hogares (EPH)	Dirección Nacional de Estadísticas, Encuestas y Censos (DNEEC)	4,464

Source: authors' elaboration based on the OSILAC ICT Statistical Information System, <http://www.cepal.org/tic/flash/>

In order to check the robustness and sensitiveness of the econometric results, our estimation strategy follows three steps. First, we estimate independently computer and Internet Probit models. Then, Bivariate Probit is performed to take into account the correlation between the error terms of both equations. Finally, the Biprobit methodology is extended, considering computer adoption as a sample selection problem for the Internet access.

V. Estimations Results

The estimation results are organized by country: Tables 3 to 9 present the Probit Estimations for both computer and Internet adoption equations. The first column of each set of results contains the baseline estimation, to which we add sequentially the *dummy* variables (*Students*, *Work* and *Rural*) and the network effects variable in order to check the sensitiveness of the estimated coefficients. We follow this procedure for all countries. As an overall conclusion, estimation results seem to be quite robust to different specifications. Additionally, we extend the analysis for Brazil, Chile and Costa Rica by estimating Bivariate Probit models (Tables 10 to 12)¹⁷.

In this case, the decision of which Bivariate Probit model is preferred is not straightforward¹⁸. Econometrically, the Bivariate Probit is estimated simultaneously by Full Information Maximum Likelihood, and the Bivariate Probit (*Heckprobit*) with sample selection is estimated in two steps, as described in the previous section. In this sense, the former is more efficient, although, considering the sample selection characteristic of the data¹⁹, the Heckprobit methodology models better the household decisions. The main issue regarding this methodology is the identification of the selection equation (Greene, 2003). In fact, consistent estimation in *Heckprobit* model requires using at least one variable that affects the computer adoption but not the Internet access, in order to permit the proper identification of the estimated coefficient on the selectivity term.²⁰ The problem is that, empirically, this is not an easy task. We use the computer penetration rate variable ($Network_{i,C}$) in the selection equation for identification purposes.

The estimation results for Brazil confirm that income and education are positive determinants of computer and Internet adoption (see Table 3). Indeed, the coefficients associated to *Income*, *Education* are positive, significant at 1% and fairly stable across the different specifications. Additionally, the positive and significant coefficients of *Users* for both computer and Internet equations capture two different effects. First, the larger the number of potential users, the higher the household utility associated with having a computer and Internet. Second, larger households are able to spread fixed expenditures on more individuals, increasing *de facto* their per capita income. With respect to the *Students* and *dummy* variables (*Work* and *Rural*) the results

¹⁷ We include three countries in this estimation set because in these cases the likelihood functions of the Bivariate estimations converged.

¹⁸ In those countries where we only implement Probit regressions, the preferred model is the one including all the explanatory variables.

¹⁹ Both methodologies are sensitive to departures from normality in the error term. In fact, the Heckprobit estimation of ϕ in equation (11) is sensitive to normality in ϵ_i , given the construction of λ_i invokes the normal assumption ($\lambda_i = \phi(Z_i; \theta) / \Phi(Z_i; \theta)$). The non-normality in the context of bivariate probability distribution functions is more complex, and it would be much easier remaining within the two-step framework.

²⁰ In the econometric literature there is no consensus regarding this point, as some scholars argue that identification on the basis of functional form is empirically adequate. This argument, founded on the non-linearity of the Probit methodology, is not fully convincing. Furthermore, any worthwhile identification should be achieved through the use of appropriate exclusion restrictions (Puhani, 2000).

show that estimated coefficients are significant and with the *a priori* expected signs. In fact, a higher proportion of students in the household raise the probability of ownership, confirming the hypothesis that computer and Internet are often used for education purposes. Also, there is evidence of complementarities between the Internet usage at work and both the computer and Internet adoption at home, with coefficients positive and significant at 1%. This relation, which has not received enough attention in the literature, shows how earlier stages of Internet adoption process in households are strongly influenced by its use in the workplace. A possible explanation refers to the fact that individuals need some training in order to fully exploit the potentialities of the Internet. So, Internet use at work increases the utility of having it at home and then the probability for households to be connected. As expected from the descriptive statistics, household located in rural areas are less likely to own a computer and to have Internet, showing the relative difficult access to ICTs in these areas.

Interestingly, the *Network* variable is positive and significant at 1%. This suggests the presence of network effects associated to the computer and Internet adoption at federation level. Thus, households are more likely to own a computer and to have Internet access if a high percentage of people in their federative units have larger ICT penetration. Also, the magnitude of the network effects seems to be higher for Internet than for computer. This fact can be interpreted considering the nature of the Internet technology itself, which is increasingly more useful as the Net is diffused in an area.

The Bivariate Probit estimations for Brazil are displayed in Table 10. Regardless of some differences in the size of the coefficients – they are relatively lower for the Internet equation in the Bivariate Probit model with sample selection with respect to the Probit estimations –the results are quite similar in their implications. Strikingly, the estimations for the Bivariate Probit and *Heckprobit* models show that, while both equations are in fact correlated, there is not a statistical selection problem between computer and Internet decisions. Given the nature of these results, we take as our preferred estimation for Brazil the Bivariate Probit model.

The Probit estimation for Chile are displayed in Table 4. Similarly to Brazil, estimated coefficients are consistent for the different specifications. For instance, variables such as *Income*, *Education*, and *Users* are relevant determinants of both computer and Internet adoption. The variable *Students* and *Work* and *Rural* dummies are also significant at 1% and with the expected sign for the computer adoption. Indeed, households with higher proportion of students, located in urban areas and in which at least one member of the households uses Internet at work are more likely to have computer. In the case of Internet adoption, the results are similar with the only exception of the *Work* variable coefficient, which is negative and significant at 10%. This suggests that, in Chile, using Internet at work may be a good substitute for being connected at

home. In other words, people who are on-line at office may present a lower utility to be connected also at home. Additionally, the Probit results confirm that there are some network effects that influence both computer and Internet adoption. One important detail is that, once it is included the network effect variable in the regressions, the coefficients associated to the *Rural* variable reduce their magnitude. Intuitively, we think that the *Network* variable may capture some of the characteristics of the rural areas, introducing some difficulties in isolating their specific effect.

Table 11 presents the estimation results by applying the Bivariate Probit procedures in Chile. In both cases, the estimates clearly confirm that the two equations are correlated, and that there is a sample selection problem that must be taken into account. In fact, the (estimated) correlation of the two error terms ρ is positive (0.99 and 0.80) and statistically different from zero²¹. This implies that unobservables affecting the computer adoption are positively correlated to unobservables affecting Internet adoption. Also in this case the results largely confirm those obtained with the Probit estimations, including the negative and significant estimated coefficient of the *Work* variable. Given that the estimation procedures confirm the sample selection problem, our preferred model in the case of Chile is the *Heckprobit* model.

In order to avoid repetitive result descriptions and considering the robustness of the estimations, we briefly comment the results regarding the remaining countries, emphasizing only those that are remarkable or intuitively not expected *a priori*. In Costa Rica, for example, the results concerning *Income*, *Education*, *Users*, *Rural* and *Network* variables are expected. However, it is noticeable that the use of Internet at work does not affect the use of Internet at home; being the coefficient associated to the *Work* variable not significant. The Bivariate Probit estimations reflect the correlated structure and the sample selection problem of the data. Then, our preferred estimation corresponds to the *Heckprobit* model. The *Heckprobit* results confirm the Probit results and also the non-relevance of the *Work dummy* variable. Also in the case of El Salvador, the Probit estimations show that traditional variables such as *Income*, *Education*, *Users*, *Students*, *Work*, and *Rural* are important determinants of computer diffusion, while the network effects variable is significant, but only at 10%. In the case of Internet adoption, the results point out that *Student* and *Work* variables are not relevant drivers of technology diffusion. Again, the network effects are significant only at the lowest confidence level. Probably, the extremely low penetration rates of ICTs in El Salvador have not reached that minimum level necessary to make network effects a stronger driver of adoption.

Honduras estimation results show that all variables are significant at 1% and they are rather stable across specifications. In Mexico, similarly to the Chilean case, the inclusion of the

²¹ The *Stata* methodology does not estimate ρ directly. To constrain ρ within its valid limits, and for numerical stability during optimization, it estimates the inverse hyperbolic tangent of ρ : $\text{Atanh } \rho = \frac{1}{2} \ln(1+\rho/1-\rho)$. Additionally, the standard error is computed using the *Delta* method (Oehlert, 1992).

network effects variable into the estimations cause a reduction on the magnitude of the estimated coefficient and of the standard deviation of the *Rural* variable. The correlation between these two variables makes difficult to disentangle rural and network effects. Finally, Paraguay estimations reflect the likely results concerning *Income* and *Education* (see Table 9). However, some outcomes must be mentioned: *Users* variable does not affect the Internet adoption and *Students* variable affects computer adoption but not Internet access. Furthermore, once the rural variable is added to the estimation, it proves to be an important driver for both computer and Internet adoption. Nevertheless, when the network variable is included, the estimation presents again the discussed problems with the *Rural* variable. In fact, in the Internet equation the Rural variable is not significant anymore. As discussed in Grazzi and Vergara (2008) this should be subject of further research.

Given the nature of a non-linear model, the marginal effects are not directly obtainable from the estimated coefficients. For illustration purposes, we only present the marginal effects for Brazil, by using the Probit estimations (see Table 13)²². For instance, the marginal effects for the income is 0.073 for computer adoption. This implies that, on average and *ceteris paribus*, an increase of 1% in household per capita income generates a raise of 7.3% in the probability of having computer access. Similarly, households with 1% higher average education are 2% more likely to own a computer, on average and *ceteris paribus*. Also, on average and *ceteris paribus*, households located in rural areas are 3.9% and 2.6% less likely to have computer and Internet adoption, respectively. Correspondingly, households having at least one member uses Internet at work are 7.0% and 3.9% more likely to have computer and Internet adoption respectively.

Overall, the econometric evidence is reasonably consistent across the different methodologies, and there are some convincing findings (see Table 14). First, income and education are the strongest determinants of ICT access. As expected, households with higher income levels and higher average education are more likely to adopt computer and the Internet. Similarly, households with students and with a larger number of potential users present higher probability of having ICT access. Second, households located in rural areas are less likely to have ICTs access, showing their relative weak position with respect to the diffusion of technologies. In addition, geographical network effects also seem to be at work at department level and independent of the urban/rural areas. Third, except for Chile, where use of Internet at work is found to be a substitute for home access, in the other considered countries there is evidence of complementarities between use at work and access at home.

²² In a Probit model the marginal changes is a function of the rest of covariates, and it is computed commonly in the mean of the variables. In fact, the marginal effect is given by the expression $\partial \Pr(y = 1) / \partial X_k = \phi(X' \beta) \beta_k$. We compute the marginal effects at the mean of variables.

VI. Concluding Remarks

The remarkable social and economic impact of ICTs diffusion over different development dimensions value a deeper analysis of its patterns. This paper focuses on the determinants of computer adoption and Internet access at household level in seven Latin American countries. Several conclusions can be drawn from both the descriptive and the parametric analysis. First, computer and Internet penetration in Latin America is relatively low if compared with developed world. Nevertheless, there are important differences across countries, showing a high degree of heterogeneity. Second, descriptive data shows how the ICT penetration is mostly concentrated in specific income and education groups and urban areas. Thus, the diffusion of technologies seems to replicate other socio-economic inequalities. Additionally, the comparative analysis shows that countries with lower ICT diffusion levels presents higher penetration inequality across income and educational groups.

The econometric analysis reveals other important features of ICT diffusion. The traditional determinants, such as income, education, and urban/rural areas are confirmed to be relevant drivers of technology diffusion across the region. Larger households and households with students are more likely to have ICT access. Moreover, there is general evidence of the presence of complementarities between Internet use at different locations and geographical network effects, though not in all countries. Finally, network effects area found to play an important role, independently from the household location in rural or urban areas.

The importance of ICTs in the development process deserves an increasing effort by international institutions, academia and scholars to achieve a better understanding of their diffusion process. The use of microdata at household level provides an appealing framework to analyze this phenomena. In fact, its implications can clearly support the design of public policies towards to expand the benefits of ICT in all segments of population.

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Table 3
Brazil - Determinants of Computer and Internet Adoption: Probit Estimations

<i>Model</i>	<i>Computer Adoption</i>			<i>Internet Adoption</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
<i>Constant</i>	-6.930 (116.43)***	-6.684 (105.24)***	-7.084 (107.10)***	-7.407 (113.85)***	-7.115 (102.25)***	-7.589 (103.81)***
<i>Income_i</i>	0.583 (68.11)***	0.580 (63.91)***	0.544 (59.14)***	0.587 (63.33)***	0.580 (58.67)***	0.549 (54.33)***
<i>Education_i</i>	0.182 (78.74)***	0.145 (59.12)***	0.150 (59.30)***	0.188 (71.76)***	0.149 (52.93)***	0.156 (53.90)***
<i>Users_i</i>	0.163 (41.97)***	0.103 (23.63)***	0.114 (25.44)**	0.175 (41.51)***	0.117 (24.58)***	0.131 (26.36)***
<i>Students_i</i>	.	0.763 (28.38)***	0.813 (29.78)***	.	0.699 (23.77)***	0.763 (25.46)***
<i>Work_i</i>	.	0.431 (28.72)***	0.426 (28.27)***	.	0.456 (28.36)***	0.450 (27.94)***
<i>Rural_i</i>	.	-0.407 (13.23)***	-0.348 (11.15)***	.	-0.616 (12.76)***	-0.569 (11.68)***
<i>Network_{i,C}</i>	.	.	0.026 (34.37)***	.	.	0.035 (35.38)***
<i>Log-Likelihood</i>	-33,560.284	-32,311.295	-31,616.756	-27,102.608	-25,967.501	-25,262.844
<i>Wald Chi²</i>	16900.17	19502.24	18681.37	15062.88	16536.21	16140.95
<i>(Prob > Chi²)</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>Pseudo-R²</i>	0.394	0.416	0.429	0.411	0.436	0.451
<i>Observations</i>	114,961	114,961	114,961	114,959	114,959	114,959

Notes: z-statistics in absolute value with robust standard errors in parenthesis.
 * Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 4
Chile - Determinants of Computer and Internet Adoption: Probit Estimations

<i>Model</i>	<i>Computer Adoption</i>			<i>Internet Adoption</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
<i>Constant</i>	-8.496 (45.98)***	-9.403 (47.80)***	-9.529 (45.78)***	-10.192 (44.53)***	-10.992 (40.18)***	-11.101 (41.31)***
<i>Income_i</i>	0.423 (27.32)***	0.526 (29.93)***	0.514 (29.29)***	0.528 (25.26)***	0.618 (26.19)***	0.595 (25.66)***
<i>Education_i</i>	0.207 (46.55)***	0.169 (35.63)***	0.168 (35.54)***	0.188 (32.31)***	0.158 (24.98)***	0.155 (24.97)***
<i>Users_i</i>	0.162 (24.08)***	0.066 (8.89)***	0.066 (8.82)***	0.156 (20.73)***	0.084 (9.69)***	0.082 (9.51)***
<i>Students_i</i>	.	1.651 (29.43)***	1.656 (29.52)***	.	1.224 (18.90)***	1.251 (19.38)***
<i>Work_i</i>	.	0.079 (2.70)***	0.077 (2.62)***	.	-0.567 (1.73)*	-0.616 (1.89)*
<i>Rural_i</i>	.	-0.386 (16.59)***	-0.295 (12.17)***	.	-0.716 (20.73)***	-0.504 (13.90)***
<i>Network_{i,C}</i>	.	.	0.008 (7.69)***	.	.	0.019 (14.37)***
<i>Log-Likelihood</i>	-32,732.764	-30,953.202	-30,865.692	-24,670.435	-23,650.492	-23,317.691
<i>Wald Chi²</i>	4454.20	5971.33	5986.75	3512.46	4079.64	4116.67
<i>(Prob > Chi²)</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>Pseudo-R²</i>	0.299	0.337	0.339	0.312	0.340	0.350
<i>Observations</i>	73,432	73,432	73,432	73,238	73,238	73,238

Notes: z-statistics in absolute value with robust standard errors in parenthesis.
 * Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 5
Costa Rica - Determinants of Computer and Internet Adoption: Probit Estimations

<i>Model</i>	<i>Computer Adoption</i>			<i>Internet Adoption</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
<i>Constant</i>	-7.695 (23.11)***	-7.828 (21.06)***	-8.319 (22.00)***	-10.682 (21.15)***	-10.685 (19.98)***	-10.93 (20.02)***
<i>Income_i</i>	0.383 (13.39)***	0.424 (13.41)***	0.422 (13.16)***	0.574 (13.26)***	0.590 (12.95)***	0.586 (12.78)***
<i>Education_i</i>	0.207 (31.15)***	0.165 (22.40)***	0.087 (6.65)***	0.181 (19.92)***	0.163 (16.22)***	0.161 (15.91)***
<i>Users_i</i>	0.164 (14.37)***	0.093 (7.20)***	0.087 (6.65)	0.134 (8.90)***	0.109 (6.45)***	0.106 (6.21)**
<i>Students_i</i>	.	0.994 (11.53)***	1.040 (11.83)***	.	0.399 (3.91)***	0.411 (4.02)***
<i>Work_i</i>	.	0.231 (4.44)***	0.190 (3.60)***	.	0.029 (0.48)	0.002 (0.04)
<i>Rural_i</i>	.	-0.203 (5.75)***	-0.101 (2.84)***	.	-0.180 (3.57)***	-0.114 (2.23)**
<i>Network_{i,C}</i>	.	.	0.019 (11.56)***	.	.	0.028 (5.37)***
<i>Log-Likelihood</i>	-4,412.370	-4,266.933	-4,203.333	-2,408.7535	-2,390.102	-2,375.893
<i>Wald Chi²</i>	1780.09	1989.37	1997.29	1144.31	1179.22	1155.91
<i>(Prob > Chi²)</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>Pseudo-R²</i>	0.330	0.352	0.362	0.352	0.357	0.360
<i>Observations</i>	11,259	11,259	11,259	11,263	11,263	11,263

Notes: z-statistics in absolute value with robust standard errors in parenthesis.
* Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 6
El Salvador - Determinants of Computer and Internet Adoption: Probit Estimations

<i>Model</i>	<i>Computer Adoption</i>			<i>Internet Adoption</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
<i>Constant</i>	-6.607 (14.53)***	-6.363 (13.73)***	-6.486 (14.08)***	-7.581 (13.73)***	-7.513 (12.59)***	-7.665 (12.64)***
<i>Income_i</i>	0.519 (5.50)***	0.509 (5.68)***	0.510 (5.72)***	0.529 (5.99)***	0.530 (5.67)***	0.527 (5.64)***
<i>Education_i</i>	0.189 (11.82)***	0.165 (11.22)***	0.164 (11.19)***	0.201 (8.78)***	0.197 (8.07)***	0.195 (7.97)***
<i>Users_i</i>	0.137 (7.91)***	0.108 (5.73)***	0.109 (5.81)***	0.095 (2.99)***	0.081 (2.22)**	0.082 (2.25)**
<i>Students_i</i>	.	0.614 (4.77)***	0.617 (4.80)***	.	0.245 (1.14)	0.259 (1.21)
<i>Work_i</i>	.	0.449 (2.75)***	0.443 (2.73)***	.	-0.098 (0.58)***	0.102 (0.60)
<i>Rural_i</i>	.	-0.376 (3.77)***	-0.328 (3.22)***	.	-0.588 (3.25)	-0.523 (2.85)***
<i>Network_{i,C}</i>	.	.	0.014 (1.95)*	.	.	0.057 (1.71)*
<i>Log-Likelihood</i>	-2,621.023	-2,561.907	-2,558.496	-1,018.941	-1,009.487	-1,006.401
<i>Wald Chi²</i>	498.09	590.34	587.34	186.17	202.59	201.34
<i>(Prob > Chi²)</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>Pseudo-R²</i>	0.402	0.415	0.416	0.445	0.450	0.452
<i>Observations</i>	16,343	16,343	16,343	16,343	16,343	16,343

Notes: z-statistics in absolute value with robust standard errors in parenthesis.
* Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 7
Honduras - Determinants of Computer and Internet Adoption: Probit Estimations

<i>Model</i>	<i>Computer Adoption</i>			<i>Internet Adoption</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
<i>Constant</i>	-6.419 (32.84)***	-6.010 (27.98)***	-6.074 (28.22)***	-8.694 (22.10)***	-8.377 (20.22)***	-8.449 (20.36)***
<i>Income_i</i>	0.367 (14.95)***	0.349 (13.23)***	0.345 (12.99)***	0.457 (10.12)***	0.448 (9.37)***	0.439 (9.13)***
<i>Education_i</i>	0.194 (33.09)***	0.163 (26.17)***	0.160 (25.68)***	0.226 (20.44)***	0.202 (16.89)***	0.197 (16.50)***
<i>Users_i</i>	0.087 (11.08)***	0.063 (7.05)**	0.062 (6.89)***	0.089 (5.70)***	0.063 (3.60)***	0.058 (3.27)***
<i>Students_i</i>	.	0.530 (7.80)***	0.532 (7.82)***	.	0.328 (2.66)***	0.332 (2.66)***
<i>Work_i</i>	.	0.364 (6.67)***	0.336 (6.13)***	.	0.465 (6.20)***	0.411 (5.36)***
<i>Rural_i</i>	.	-0.407 (8.46)***	-0.377 (7.66)***	.	-0.544 (3.44)***	-0.494 (3.09)***
<i>Network_{i,C}</i>	.	.	0.013 (4.13)***	.	.	0.096 (4.47)***
<i>Log-Likelihood</i>	-3,459.637	-3,367.541	-3,360.1503	-817.869	-790.866	-784.131
<i>Wald Chi²</i>	2208.96	2204.15	2222.43	727.17	703.54	713.00
<i>(Prob > Chi²)</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>Pseudo-R²</i>	0.370	0.386	0.388	0.456	0.474	0.479
<i>Observations</i>	20,581	20,581	20,581	20,283	20,283	20,283

Notes: z-statistics in absolute value with robust standard errors in parenthesis.

* Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 8
Mexico - Determinants of Computer and Internet Adoption: Probit Estimations

<i>Model</i>	<i>Computer Adoption</i>			<i>Internet Adoption</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
<i>Constant</i>	-6.116 (15.61)***	-5.981 (13.91)***	-6.307 (14.24)***	-7.023 (13.54)***	-6.432 (11.48)***	-6.863 (12.16)***
<i>Income_i</i>	0.214 (4.43)***	0.232 (4.34)***	0.211 (3.88)***	0.322 (5.36)***	0.300 (4.56)***	0.277 (4.24)***
<i>Education_i</i>	4.719 (17.83)***	4.072 (14.02)***	4.117 (13.91)***	3.886 (14.06)***	3.206 (11.25)***	3.334 (11.37)***
<i>Users_i</i>	0.179 (9.04)***	0.117 (5.25)***	0.121 (5.30)***	0.155 (6.42)***	0.114 (4.06)***	0.125 (4.33)***
<i>Students_i</i>	.	1.094 (6.78)***	1.084 (6.67)***	.	0.596 (3.16)***	0.580 (3.04)***
<i>Work_i</i>	.	0.459 (4.54)***	0.454 (4.44)***	.	0.431 (4.12)***	0.424 (4.05)***
<i>Rural_i</i>	.	-0.122 (1.53)	-0.042 (0.52)	.	-0.231 (2.21)**	-0.135 (1.24)
<i>Network_{i,C}</i>	.	.	0.019 (4.14)***	.	.	0.039 (4.82)***
<i>Log-Likelihood</i>	-1,725.518	-1,651.021	-1,633.567	-1,092.258	-1,059.422	-1,036.500
<i>Wald Chi²</i>	465.85	548.32	538.51	297.45	305.30	327.11
<i>(Prob > Chi²)</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>Pseudo-R²</i>	0.291	0.322	0.329	0.277	0.299	0.314
<i>Observations</i>	4,811	4,811	4,811	4,813	4,813	4,813

Notes: z-statistics in absolute value with robust standard errors in parenthesis; * Significant at 10%; **

Significant at 5%, *** Significant at 1%.

Table 9
Paraguay - Determinants of Computer and Internet Adoption: Probit Estimations

<i>Model</i>	<i>Computer Adoption</i>			<i>Internet Adoption</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
<i>Constant</i>	-13.320 (12.83)***	-13.118 (11.66)***	-13.074 (11.72)***	-12.960 (10.67)***	-12.058 (9.13)***	-12.024 (9.02)***
<i>Income_i</i>	0.690 (8.98)***	0.693 (8.33)***	0.677 (8.18)***	0.658 (7.48)***	0.618 (6.42)***	0.606 (6.29)***
<i>Education_i</i>	0.176 (12.82)***	0.145 (9.66)***	0.142 (9.39)***	0.116 (5.54)***	0.092 (3.81)***	0.077 (3.17)***
<i>Users_i</i>	0.124 (5.91)***	0.080 (3.37)***	0.076 (3.17)***	0.055 (1.92)*	0.042 (1.27)	0.021 (0.64)
<i>Students_i</i>	.	0.828 (4.92)***	0.892 (5.23)***	.	-0.026 (0.10)	0.131 (0.47)
<i>Work_i</i>	.	0.300 (2.51)**	0.272 (2.26)**	.	0.329 (2.10)**	0.311 (1.88)*
<i>Rural_i</i>	.	-0.311 (2.81)***	-0.186 (1.60)*	.	-0.329 (2.10)**	-0.316 (1.08)
<i>Network_{i,C}</i>	.	.	0.017 (3.98)***	.	.	0.078 (4.81)***
<i>Log-Likelihood</i>	-776.752	-752.322	-746.266	-255.445	-249.223	-237.133
<i>Wald Chi²</i>	417.69	438.72	476.56	140.63	149.84	194.78
<i>(Prob > Chi²)</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>Pseudo-R²</i>	0.408	0.427	0.431	0.336	0.352	0.383
<i>Observations</i>	4,461	4,461	4,461	4,461	4,461	4,461

Notes: z-statistics in absolute value with robust standard errors in parenthesis; * Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 10
Brazil - Determinants of Computer Adoption and Internet Access: Bivariate Probit Estimations

<i>Method</i>	<i>Bivariate Probit</i>		<i>Bivariate Probit w/ sample selection (HeckProbit)</i>	
	Computer (1)	Internet (2)	Computer (3)	Internet (4)
Variables				
Constant	-7.055 (109.02)***	-7.572 (106.34)***	-7.084 (107.07)***	-3.172 (5.04)***
<i>Income_i</i>	0.540 (60.25)***	0.554 (55.67)***	0.544 (59.07)***	0.293 (6.86)***
<i>Education_i</i>	0.150 (59.30)***	0.153 (55.45)***	0.150 (59.29)***	0.076 (6.10)***
<i>Users_i</i>	0.115 (26.00)***	0.122 (23.47)***	0.114 (25.32)***	0.068 (5.27)***
<i>Students_i</i>	0.808 (29.87)***	0.750 (25.21)***	0.813 (29.77)***	0.259 (3.52)***
<i>Work_i</i>	0.425 (28.28)***	0.449 (28.14)***	0.426 (28.27)***	0.254 (6.40)***
<i>Rural_i</i>	-0.354 (11.38)***	-0.582 (12.38)***	-0.347 (11.13)***	-0.655 (8.24)***
<i>Network_{i,C}</i>	0.026 (34.83)***	.	0.026 (34.38)***	.
<i>Network_{i,I}</i>	.	0.036 (36.52)***	.	0.027 (9.32)***
<i>Log-Likelihood</i>	-19,363,638		-19,400,000	
$\rho = Cov(\varepsilon_1, \varepsilon_2)$	0.99		-0.05	
<i>Atanh</i> $\rho = \frac{1}{2} \ln(1+\rho/1-\rho)$	3.738 (17.36)***		-0.054 (0.46)	
<i>Wald Chi²</i> (<i>Prob > Chi²</i>)	21603.92 (0.000)		142.33 (0.000)	
<i>Wald Test of indep. eqs. ($\rho=0$)</i> <i>Chi² (1)</i> (<i>Prob > Chi²</i>)	301.323 (0.000)		0.22 (0.642)	
<i>Censored observations</i>	.		94,725	
<i>Uncensored observations</i>	.		20,234	
<i>Observations</i>	114,959		114,959	

Notes: z-statistics in absolute value with robust standard errors in parenthesis; * Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 11
Chile - Determinants of Computer Adoption and Internet Access: Bivariate Probit Estimations

<i>Method</i>	<i>Bivariate Probit</i>		<i>Bivariate Probit w/ sample selection (HeckProbit)</i>	
	Computer (1)	Internet (2)	Computer (3)	Internet (4)
Variables				
Constant	-9.602 (45.78)***	-11.059 (43.67)***	-9.619 (46.43)***	-10.898 (28.23)***
<i>Income_i</i>	0.515 (29.17)***	0.591 (27.19)***	0.517 (29.60)***	0.592 (23.74)***
<i>Education_i</i>	0.168 (35.74)***	0.155 (27.06)***	0.168 (35.65)***	0.146 (14.10)***
<i>Users_i</i>	0.069 (9.53)***	0.078 (8.50)***	0.069 (9.22)***	0.078 (7.20)***
<i>Students_i</i>	1.635 (29.92)***	1.242 (19.42)***	1.652 (29.39)***	1.091 (7.62)***
<i>Work_i</i>	0.729 (2.49)**	-0.058 (1.83)*	0.074 (2.53)**	-0.090 (2.22)**
<i>Rural_i</i>	-0.296 (12.13)***	-0.496 (13.86)***	-0.300 (12.08)***	-0.517 (12.41)***
<i>Network_{i,C}</i>	0.009 (9.13)***	.	0.009 (8.01)***	.
<i>Network_{i,I}</i>	.	0.021 (16.17)***	.	0.024 (11.01)***
<i>Log-Likelihood</i>	-2,633,513.2		-2,633,113	
$\rho = Cov(\varepsilon_1, \varepsilon_2)$	0.99		0.80	
<i>Atanh</i> $\rho = \frac{1}{2} \ln(1+\rho/1-\rho)$	4.121 (10.41)***		1.087 (3.06)***	
<i>Wald Chi² (9)</i> (<i>Prob > Chi²</i>)	7387.55 (0.000)		2768.57 (0.000)	
<i>Wald Test of indep. eqs. ($\rho=0$)</i> <i>Chi² (1)</i> (<i>Prob > Chi²</i>)	108.316 (0.000)		9.37 (0.002)	
<i>Censored observations</i>	.		58,411	
<i>Uncensored observations</i>	.		14,827	
<i>Observations</i>	73,238		73,238	

Notes: z-statistics in absolute value with robust standard errors in parenthesis; Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 12

Costa Rica - Determinants of Computer Adoption and Internet Access: Bivariate Probit Estimations

<i>Method</i>	<i>Bivariate Probit</i>		<i>Bivariate Probit w/ sample selection (HeckProbit)</i>	
	Computer (1)	Internet (2)	Computer (3)	Internet (4)
Variables				
Constant	-8.293 (22.00)***	-10.849 (20.74)***	-8.294 (22.01)***	-10.851 (20.75)***
<i>Income_i</i>	0.419 (13.04)***	0.579 (13.00)***	0.418 (13.05)***	0.579 (13.02)***
<i>Education_i</i>	0.162 (21.84)***	0.163 (15.85)***	0.162 (21.77)***	0.163 (15.72)***
<i>Users_i</i>	0.091 (6.96)***	0.091 (5.00)*	0.091 (6.96)***	0.091 (4.99)***
<i>Students_i</i>	1.028 (11.90)***	0.382 (83.79)***	1.028 (11.90)***	0.381 (3.75)***
<i>Work_i</i>	0.189 (3.60)***	0.027 (0.46)***	0.189 (3.60)***	0.026 (0.44)
<i>Rural_i</i>	-0.103 (2.92)***	-0.141 (2.84)***	-0.103 (2.92)***	-0.142 (2.84)***
<i>Network_{i,C}</i>	0.019 (11.80)***	.	0.019 (11.79)***	.
<i>Network_{i,I}</i>	.	0.032 (6.24)***	.	0.032 (6.14)***
<i>Log-Likelihood</i>	-581,630.44		-581,628.7	
$\rho = Cov(\varepsilon_1, \varepsilon_2)$	0.99		0.95	
<i>Atanh $\rho = 1/2 \ln(1+\rho/1-\rho)$</i>	3.411 (8.19)***		1.869 (4.85)***	
<i>Wald Chi² (9)</i> (<i>Prob > Chi²</i>)	2484.41 (0.000)		1131.44 (0.000)	
<i>Wald Test of indep. eqs. ($\rho=0$)</i> <i>Chi² (1)</i> (<i>Prob > Chi²</i>)	67.085 (0.000)		23.51 (0.000)	
<i>Censored observations</i>	.		8,838	
<i>Uncensored Observations</i>	.		2,421	
<i>Observations</i>	11,259		11,259	

Notes: z-statistics in absolute value with robust standard errors in parenthesis,
Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 13
Marginal Effects - Brazil^a

<i>Variables</i>	<i>Computer</i> (1)	<i>Internet</i> (2)
<i>Income_i</i>	0.073 (52.61)***	0.036 (38.34)***
<i>Education_i</i>	0.020 (61.42)***	0.010 (43.28)***
<i>Users_i</i>	0.015 (26.74)***	0.008 (26.15)***
<i>Students_i</i>	0.110 (28.66)***	0.504 (22.81)***
<i>Work_i</i>	0.070 (22.42)***	0.039 (19.49)***
<i>Rural_i</i>	-0.039 (14.03)***	-0.026 (19.22)***
<i>Network_{i,C}</i>	0.003 (32.08)***	0.002 (28.01)***

Source: Authors elaboration based on column (5) and (6) of table 10; ^a In the case of dummy variables, the marginal effect correspond to a discrete change of the variable from 0 to 1, *i.e.* impact effects; Coefficients z-statistics with robust standard errors in parenthesis, * Significant at 10%; ** Significant at 5%, *** Significant at 1%.

Table 14
Determinants of Computer and Internet Adoption: Resume Table

<i>Country</i> Variable	<i>Brazil</i>	<i>Chile</i>	<i>Costa Rica</i>	<i>El Salvador</i>	<i>Honduras</i>	<i>Mexico</i>	<i>Paraguay</i>
	<i>Computer Adoption</i>						
<i>Income_i</i>	+	+	+	+	+	+	+
<i>Education_i</i>	+	+	+	+	+	+	+
<i>Users_i</i>	+	+		+	+	+	+
<i>Students_i</i>	+	+	+	+	+	+	+
<i>Work_i</i>	+	+	+	+	+	+	+
<i>Rural_i</i>	-	-	-	-	-		-
<i>Network_{i,C}</i>	+	+	+	+	+	+	+
	<i>Internet Adoption</i>						
<i>Income_i</i>	+	+	+	+	+	+	+
<i>Education_i</i>	+	+	+	+	+	+	+
<i>Users_i</i>	+	+	+	+	+	+	
<i>Students_i</i>	+	+	+		+	+	
<i>Work_i</i>	+	-			+	+	+
<i>Rural_i</i>	-	-	-	-	-		-
<i>Network_{i,I}</i>	+	+	+	+	+	+	+

Source: Author's elaboration based on preferred estimation model for each country.

Annex 1.
Data Summary - Brazil

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Std. deviation</i>	<i>Min.</i>	<i>Max.</i>
<i>Pr(Computer=1)</i>	Dichotomous computer adoption variable: 1:yes; 0: no.	0.19	0.39	0	1
<i>Pr(Internet=1)</i>	Dichotomous internet adoption variable: 1:yes; 0: no.	0.14	0.34	0	1
<i>Income_i</i>	Log _n of equivalent household income.	6.47	1.03	-0.55	12.55
	Log _n of household equivalent income if <i>Pr(Computer=1)</i>	7.53	0.92	2.01	12.55
	Log _n of household equivalent income if <i>Pr(Internet=1)</i>	7.69	0.88	2.05	12.55
<i>Education_i</i>	Average of adults education years (age>17)	6.89	4.07	0	17
	Average of adults education years (age>17) if <i>Pr(Computer=1)</i>	11.22	3.06	0	17
	Average of adults education years (age>17) if <i>Pr(Internet=1)</i>	11.73	2.86	0	17
<i>Users_i</i>	Number of potential users of ICTs (age>6).	3.13	1.55	1	19
<i>Network_{i,C}</i>	Percentage of households with computer, by Federative Unit ^a .	18.53	8.72	4.06	36.35
<i>Network_{i,I}</i>	Percentage of households with Internet connection, by Federative Unit ^b .	13.63	7.21	2.06	28.61
<i>Students_i</i>	Proportion of students in the household	0.23	0.25	0	1
<i>Work_i</i>	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.	0.18	0.39	0	1
<i>Rural_i</i>	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.	0.15	0.36	0	1

Source: Authors' calculation based on the *Pesquisa Nacional por Amostra de Domicílios (PNAD)* of Brazil, 2005.

^a Brazil is divided in 27 Federative Units: Acre, Alagoas, Amapa, Amazonas, Bahia, Ceara, Distrito Federal, Espirito Santo, Goias, Maranhao, Mato Grosso, Mato Grosso do Sul, Minas Gerais, Para, Paraiba, Parana, Pernambuco, Piaui, Rio de Janeiro, Rio Grande do Norte, Rio Grande do Sul, Rondonia, Roraima, Santa Catarina, Sao Paulo, Sergipe, Tocantins.

Data Summary – Chile

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Std. deviation</i>	<i>Min.</i>	<i>Max.</i>
<i>Pr(Computer=1)</i>	Dichotomous computer adoption variable: 1:yes; 0: no.	0.33	0.47	0	1
<i>Pr(Internet=1)</i>	Dichotomous internet adoption variable: 1:yes; 0: no.	0.19	0.39	0	1
<i>Income_i</i>	Log _n of equivalent household income.	12.32	0.91	5.52	17.29
	Log _n of household equivalent income if <i>Pr(Computer=1)</i>	12.88	0.90	7.18	16.94
	Log _n of household equivalent income if <i>Pr(Internet=1)</i>	13.14	0.90	7.18	16.69
<i>Education_i</i>	Average of adults education years (age>17)	10.03	3.71	0	20
	Average of adults education years (age>17) if <i>Pr(Computer=1)</i>	12.69	2.75	0	20
	Average of adults education years (age>17) if <i>Pr(Internet=1)</i>	13.33	2.61	0	20
<i>Users_i</i>	Number of potential users of ICTs (age>6).	3.41	1.56	1	15
<i>Network_{i,C}</i>	Percentage of households with computer, by Province ^a .	33.13	10.20	3.57	58.38
<i>Network_{i,I}</i>	Percentage of households with Internet connection, by Province ^b .	19.16	9.39	1.30	30.54
<i>Students_i</i>	Proportion of students in the household	0.22	0.23	0	1
<i>Work_i</i>	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.	0.19	0.39	0	1
<i>Rural_i</i>	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.	0.13	0.34	0	1

Source: Authors' calculation based on the *Encuesta de Caracterización Socioeconómica Nacional (CASEN)* of Chile, 2006.

^a Chile is divided in 50 Provinces.

Data Summary - Costa Rica

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Std. deviation</i>	<i>Min.</i>	<i>Max.</i>
<i>Pr(Computer=1)</i>	Dichotomous computer adoption variable: 1:yes; 0: no.	0.27	0.45	0	1
<i>Pr(Internet=1)</i>	Dichotomous internet adoption variable: 1:yes; 0: no.	0.10	0.30	0	1
<i>Income_i</i>	Log _n of equivalent household income.	11.84	0.92	7.82	15.37
	Log _n of household equivalent income if <i>Pr(Computer=1)</i>	12.52	0.75	8.17	15.37
	Log _n of household equivalent income if <i>Pr(Internet=1)</i>	12.87	0.69	8.17	15.37
<i>Education_i</i>	Average of adults education years (age>17)	8.10	3.83	0	19
	Average of adults education years (age>17) if <i>Pr(Computer=1)</i>	11.56	3.11	0	19
	Average of adults education years (age>17) if <i>Pr(Internet=1)</i>	12.96	2.73	3.5	19
<i>Users_i</i>	Number of potential users of ICTs (age>6).	3.40	1.59	1	14
<i>Network_{i,C}</i>	Percentage of households with computer, by Planning Region ^a .	26.57	10.70	10.44	34.57
<i>Network_{i,I}</i>	Percentage of households with Internet connection, by Planning Region ^b .	10.03	4.90	3.17	13.70
<i>Students_i</i>	Proportion of students in the household	0.27	0.26	0	1
<i>Work_i</i>	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.	0.16	0.37	0	1
<i>Rural_i</i>	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.	0.40	0.49	0	1

Source: Authors' calculation based on the *Encuesta de Hogares de propósitos múltiples (EHPM)* of Costa Rica, 2005.

^a Costa Rica is divided in 6 Planning Regions: Región Central, Chorotega, Pacífico Central, Brunca, Huetar Atlántica, Huetar Norte.

Data Summary - El Salvador

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Std. deviation</i>	<i>Min.</i>	<i>Max.</i>
<i>Pr(Computer=1)</i>	Dichotomous computer adoption variable: 1:yes; 0: no.	0.07	0.26	0	1
<i>Pr(Internet=1)</i>	Dichotomous internet adoption variable: 1:yes; 0: no.	0.02	0.15	0	1
<i>Income_i</i>	Log _n of equivalent household income.	5.08	0.83	0.35	8.91
	Log _n of household equivalent income if <i>Pr(Computer=1)</i>	6.17	0.94	0.69	8.91
	Log _n of household equivalent income if <i>Pr(Internet=1)</i>	6.54	0.83	1.99	8.67
<i>Education_i</i>	Average of adults education years (age>17)	6.63	4.43	0	22
	Average of adults education years (age>17) if <i>Pr(Computer=1)</i>	13.11	3.39	0	22
	Average of adults education years (age>17) if <i>Pr(Internet=1)</i>	14.97	2.93	0	22
<i>Users_i</i>	Number of potential users of ICTs (age>6).	3.58	1.84	1	17
<i>Network_{i,C}</i>	Percentage of households with computer, by Department ^a .	7.57	4.24	1.42	12.67
<i>Network_{i,I}</i>	Percentage of households with Internet connection, by Department ^b .	2.38	1.63	0.09	4.13
<i>Students_i</i>	Proportion of students in the household	0.24	0.24	0	1
<i>Work_i</i>	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.	0.24	0.15	0	1
<i>Rural_i</i>	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.	0.37	0.48	0	1

Source: Authors' calculation based on the *Encuesta de Hogares de Propósitos Múltiples. (EHPM)* of El Salvador, 2005.

^a El Salvador is divided in 14 Departments: Ahuachapán, Cabañas, Chalatenango, Cuscatlán, La Libertad, La Paz, La Unión, Morazán, San Miguel, San Salvador, San Vicente, Santa Ana, Sonsonate, Usulután.

Data Summary - Honduras

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Std. deviation</i>	<i>Min.</i>	<i>Max.</i>
<i>Pr(Computer=1)</i>	Dichotomous computer adoption variable: 1:yes; 0: no.	0.08	0.27	0	1
<i>Pr(Internet=1)</i>	Dichotomous internet adoption variable: 1:yes; 0: no.	0.01	0.12	0	1
<i>Income_i</i>	Log _n of equivalent household income.	7.55	1.16	-3.41	14.84
	Log _n of household equivalent income if <i>Pr(Computer=1)</i>	8.89	0.97	2.12	13.07
<i>Education_i</i>	Log _n of household equivalent income if <i>Pr(Internet=1)</i>	9.41	0.94	5.24	13.07
	Average of adults education years (age>17)	6.39	3.40	0	22
<i>Users_i</i>	Average of adults education years (age>17) if <i>Pr(Computer=1)</i>	11.74	3.40	1	22
	Average of adults education years (age>17) if <i>Pr(Internet=1)</i>	13.78	2.64	5	22
<i>Network_{i,C}</i>	Number of potential users of ICTs (age>6).	4.03	2.00	1	18
<i>Network_{i,I}</i>	Percentage of households with computer, by Department ^a .	7.61	5.27	1.68	16.75
	Percentage of households with Internet connection, by Department ^b .	1.43	1.43	0	3.77
<i>Students_i</i>	Proportion of students in the household	0.28	0.24	0	1
<i>Work_i</i>	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.	0.03	0.18	0	1
<i>Rural_i</i>	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.	0.51	0.50	0	1

Source: Authors' calculation based on the *Encuesta Permanente de Hogares de Propósitos Múltiples* (EPHPM) of Honduras, 2006.

^a Honduras is divided in 18 Departments: Atlántida, Choluteca, Colón, Comayagua, Copán, Cortés, El Paraíso, Francisco Morazán, Gracias a Dios, Intibucá, Islas de la Bahía, La Paz, Lempira, Ocotepeque, Olancho, Santa Bárbara, Valle, Yoro.

Data Summary - Mexico

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Std. deviation</i>	<i>Min.</i>	<i>Max.</i>
<i>Pr(Computer=1)</i>	Dichotomous computer adoption variable: 1:yes; 0: no.	0.21	0.40	0	1
<i>Pr(Internet=1)</i>	Dichotomous internet adoption variable: 1:yes; 0: no.	0.10	0.30	0	1
<i>Income_i</i>	Log _n of equivalent household income.	7.83	0.99	2.52	11.92
	Log _n of household equivalent income if <i>Pr(Computer=1)</i>	8.44	0.94	3.91	11.92
<i>Education_i</i>	Log _n of household equivalent income if <i>Pr(Internet=1)</i>	8.68	0.93	5.37	10.90
	Index of household education	0.55	0.18	0	1
<i>Users_i</i>	Index of household education if <i>Pr(Computer=1)</i>	0.73	0.15	0.2	1
	Index of household education if <i>Pr(Internet=1)</i>	0.76	0.14	0.33	1
<i>Network_{i,C}</i>	Number of potential users of ICTs (age>6).	3.48	1.74	1	15
<i>Network_{i,I}</i>	Percentage of households with computer, by Federative Unit ^a .	20.62	8.06	5.92	37.59
	Percentage of households with Internet connection, by Federative Unit ^b .	10.05	5.47	1.10	21.04
<i>Students_i</i>	Proportion of students in the household	0.26	0.25	0	1
<i>Work_i</i>	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.	0.13	0.34	0	1
<i>Rural_i</i>	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.	0.57	0.50	0	1

Source: Authors' calculation based on the *Encuesta Nacional sobre Disponibilidad y Uso de las Tecnologías de la Información en los Hogares* (ENDUTIH) of Mexico, 2006.

^a Mexico is divided in 32 Federative Units: Aguascalientes, Baja California, Baja California Sur, Campeche, Chiapas, Chihuahua, Coahuila de Zaragoza, Colima, Distrito Federal*, Durango, Guanajuato, Guerrero, Hidalgo, Jalisco, Mexico, Michoacan de Ocampo, Morelos, Nayarit, Nuevo Leon, Oaxaca, Puebla, Queretaro de Arteaga, Quintana Roo, San Luis Potosí, Sinaloa, Sonora, Tabasco, Tamaulipas, Tlaxcala, Veracruz-Llave, Yucatan, Zacatecas.

Data Summary – Paraguay

<i>Variable</i>	<i>Description</i>	<i>Mean</i>	<i>Std. deviation</i>	<i>Min.</i>	<i>Max.</i>
$Pr(Computer=1)$	Dichotomous computer adoption variable: 1:yes; 0: no.	0.09	0.28	0	1
$Pr(Internet=1)$	Dichotomous internet adoption variable: 1:yes; 0: no.	0.02	0.13	0	1
$Income_i$	Log_n of equivalent household income.	13.47	0.96	9.58	17.74
	Log_n of household equivalent income if $Pr(Computer=1)$	14.69	0.74	12.03	17.52
	Log_n of household equivalent income if $Pr(Internet=1)$	15.04	0.67	13.19	16.74
$Education_i$	Average of adults education years (age>17)	7.76	3.92	0	18
	Average of adults education years (age>17) if $Pr(Computer=1)$	13.07	2.79	3	18
	Average of adults education years (age>17) if $Pr(Internet=1)$	13.66	2.57	3	2.3
$Users_i$	Number of potential users of ICTs (age>6).	3.79	1.95	1	15
$Network_{i,C}$	Percentage of households with computer, by Department ^a .	8.67	7.12	0	26.88
$Network_{i,I}$	Percentage of households with Internet connection, by Department ^b .	1.70	2.68	0	9.55
$Students_i$	Proportion of students in the household	0.27	0.24	0	1
$Work_i$	Dichotomous variable; 1 if at least one individual of the household uses Internet at work, 0 otherwise.	0.06	0.25	0	1
$Rural_i$	Dichotomous variable; 1 if the household is located at rural area, 0 otherwise.	0.39	0.49	0	1

Source: Authors' calculation based on the *Encuesta Permanente de Hogares (EPH)*, 2005 of Paraguay.

^a Paraguay is divided in 15 departments: Asunción, Concepción, San Pedro, Cordillera, Guairá, Caaguazú, Caazapá, Itapúa, Misiones, Paraguari, Alto Paraná, Central, Ñeembucú, Amambay, Canindeyú, Presidente Hayes.