Demand price elasticity of mobile voice communication: A comparative firm level data analysis

Fayçal Sawadogo

Demand price elasticity of mobile voice communication: A comparative firm level data analysis

Fayçal SAWADOGO[1,2*]

[1] Université Clermont-Auvergne, CNRS, IRD, CERDI, F-63000 Clermont-Ferrand

[2] Fondation pour les Etudes et recherches sur le Développement International (FERDI), F-63000 Clermont-Ferrand

Abstract

This study estimates the price elasticity of mobile voice communication in developed and developing countries using quarterly operator data from 2000 to 2017. Using a dynamic panel model through system-GMM, the study finds that the demand price elasticity is higher for operators in developed countries. Controlling for cross-price elasticity with internet data prices reveals that voice communication is a substitute for internet data usage in developed countries. Another important finding is that, for operators in developing countries, the price elasticity decreases with market development level, whereas it increases for those in developed countries. Demand for mobile voice communication is thus more sensitive to price changes in the less penetrated markets in developing countries and the mature markets in developed countries. Furthermore, over time, price elasticity has decreased across operators in developing countries, highlighting the need for updating regulatory frameworks for the telecommunications sector to reflect the sector's various developments. In addition, when formulating regulatory policies, some important economic factors, such as income level and domestic market characteristics, should be considered to avoid losses in consumer welfare. The high estimated price elasticities suggest that operators do not have an obvious interest in engaging in collusive behavior that would hinder competition. Moreover, since there is no differential effect due to operators' positions or market shares, asymmetric regulation of the dominant operators should be avoided.

Keywords: Econometric demand model; Dynamic panel analysis; Telecommunications services; Comparative analysis.

JEL Codes: C23; C36; L96; O57.

*corresponding author: faycal.sawadogo@uca.fr, 26 Avenue Leon Blum, 63000 Clermont-Ferrand, France

I. Introduction

Since the 2000s, the mobile telecommunications sector has undergone unprecedented development in many developing countries, with a proliferation of "greenfield" operations and the opening up of the sector to competition. This has been accompanied by the creation of regulatory agencies that have become independent over time in most countries (ITU, 2018). All these factors have contributed to a significant decrease in communication tariffs in the sector, increasing consumer consumption, with concomitant welfare gains.

However, the OECD (2012), in a study on Mexico's telecommunications services, concludes that the high prices due to the sector's high concentration have led to losses in consumer welfare from 2005 to 2009. Hausman and Ros (2013), in response to the OECD study, contend that concentration and high market share are a necessary but not sufficient condition for a dominant position of power and higher prices; they show, through an estimation of the demand price elasticity, that the consumer surplus has been affected positively in the period. They argue that, in addition to competition, regulatory agencies should consider various more important factors, such as market share and the price elasticities of demand and supply. In addition, Jeanjean (2015) shows that investment in new technologies is more decisive in lowering prices than competition, which has a limited effect over time.

From another point of view, some authors, such as Matheson and Petit (2020), argue that mobile network operators (MNOs) extract a sort of rent through their exploitative behavior due to limited competition. This implies tacit collusive behavior among MNOs and some failures in regulatory processes. Carlton and Perloff (2004) and Dewenter and Haucap (2008) argue that the demand price elasticity in an industry is an important indicator of companies' decision to engage in collusive behavior. Indeed, low price elasticities are a motivation to engage in collusive behavior, as operators are afforded the choice to set higher prices without losing demand, thus increasing their mark ups. Conversely, higher price elasticities are not conducive to collusion due to the possible "cheating" problem that may result in a great loss to the cheated firm. From all these studies, it may be noted that demand price elasticity is an important factor in an analysis of the demand for telecommunication services through regulatory processes, consumer welfare, and operators' behaviors.

Many studies on the telecommunications sector have addressed the question of the demand for telecommunications services in the economics literature (Roller and Waverman, 2001; Martins, 2003; Waverman et al., 2005; Madden et al., 2004; Garbacz and Thompson, 2007; Dewenter and Haucap, 2008; Hausman and Ros, 2013). Some have considered market or operator characteristics (Koutroumpis et al., 2011; Kathuria et al., 2009; Karacuka et al., 2011; Dewenter and Haucap, 2008).

However, most of these studies were based on operator data at country level and did not allow comparisons between different markets following the same approach. Furthermore, they used pre-2012 data, whereas the sector had undergone significant development in recent years.

Therefore, using quarterly mobile operator data from 2000 to 2017, taken from the GSMA Intelligence database, the objective of my study is to analyze demand price elasticity dynamics for operators in both developing and developed countries, and the extent to which these estimates could vary, depending on such factors as the country of location income level, region, market penetration level, or some other operator characteristics. Moreover, I analyze the relationship between voice communication and internet data usage, filling an important gap in the literature on this issue. To determine short- and long-run price elasticities, I consider a dynamic panel model that I estimate using a system-GMM that produces more efficient and consistent estimates than the first difference GMM. I find that demand for mobile voice communication is more elastic in developed countries, due to their market characteristics. Furthermore, my results show that mobile voice communication is a substitute for internet data usage only in these countries. An important finding is that the demand price elasticity has decreased over the years in developing countries, and that it decreases with market development level. In developed countries, it has remained constant over the years, and increases with market development level. Concerning debates on collusion behaviors or dominant market position power abuse, my results show that there is no differential price elasticity due to operators' market shares or positions, suggesting that asymmetric regulation should be avoided, as proposed by Hausman and Ros (2013). Considering the first period of estimation (2000–2008), my results confirm the findings of previous studies (Martins, 2003; Lee and Lee, 2006; Kathuria et al., 2009; Koutroumps et al., 2011; Hakim and Neaime, 2014).

The remainder of the paper is organized as follows: Section 2 summarizes some stylized facts and presents a brief literature review. Section 3 presents the empirical strategy and the data used, while Section 4 is devoted to the results. Finally, Section 5 concludes with a discussion of the findings.

II. Stylized facts and literature review

1. Stylized facts

Over the years, the number of minutes of use per subscriber has increased in all countries, depending on their income level (figure 1.A). This individual demand has been lower for operators in low income countries. I observe that operators in developing African countries have faced lower minutes of use per subscriber since 2009 (figure 1.B). The decreasing trend is due to the important growth of subscribers that has occurred since 2001. For operators in developed countries (figure 1.C), the individual demand for minutes of use is lower for those located in Oceania. The peaks observed in America between 2006 and 2010 are due to the unavailability of data for several operators. For 2007, for example, I only have data for one operator, with minutes of use per subscriber of less than 1000; for 2008, I have data for 3 operators, with minutes of use per subscriber of, respectively, approximately 2000, 4000, and 6000.

Figure 1 presents the evolution of the average operator's minutes of use per subscriber and price of a minute of communication, depending on country of location level of income and region. Figure 1.D shows the evolution of the price of a minute of call, depending on countries' income level. Prior to 2009, the price evolution trend was not entirely stable, and the average price of a minute remained above USD 0.05, with high income countries' operators charging higher prices. In the period after 2009, prices generally followed a decreasing trend and were below USD 0.05 for operators in developing countries, with those in low and upper-middle income countries charging lower and similar prices. Operators in high income countries still charged higher effective prices. Considering regions in figure 1.E for operators in developing countries, I note two periods, 2000–2008 and 2009–2017, with an ambiguous evolution for the first period. At the end of this period, operators in Africa and Europe charged higher prices for a minute of call. In the second period, prices decreased in all regions but remained higher for African operators. In addition, Asian and European operators for which prices had significantly decreased charged lower prices. For operators in developed countries, those located in Europe and Oceania had charged higher effective prices prior to 2012.

This decreasing trend can be explained by many factors, such as competition in the markets, the presence of regulatory authorities that provide a framework for price setting, reduced operator costs, and technological progress (innovation). However, Jeanjean (2015), studying 20 countries in the period 2006–2012, argues that the ongoing investments in successive generations of technology (1G, 2G, 3G, and 4G) explain this drop in prices, as operators' traffic increases much more than their revenues (turnover).

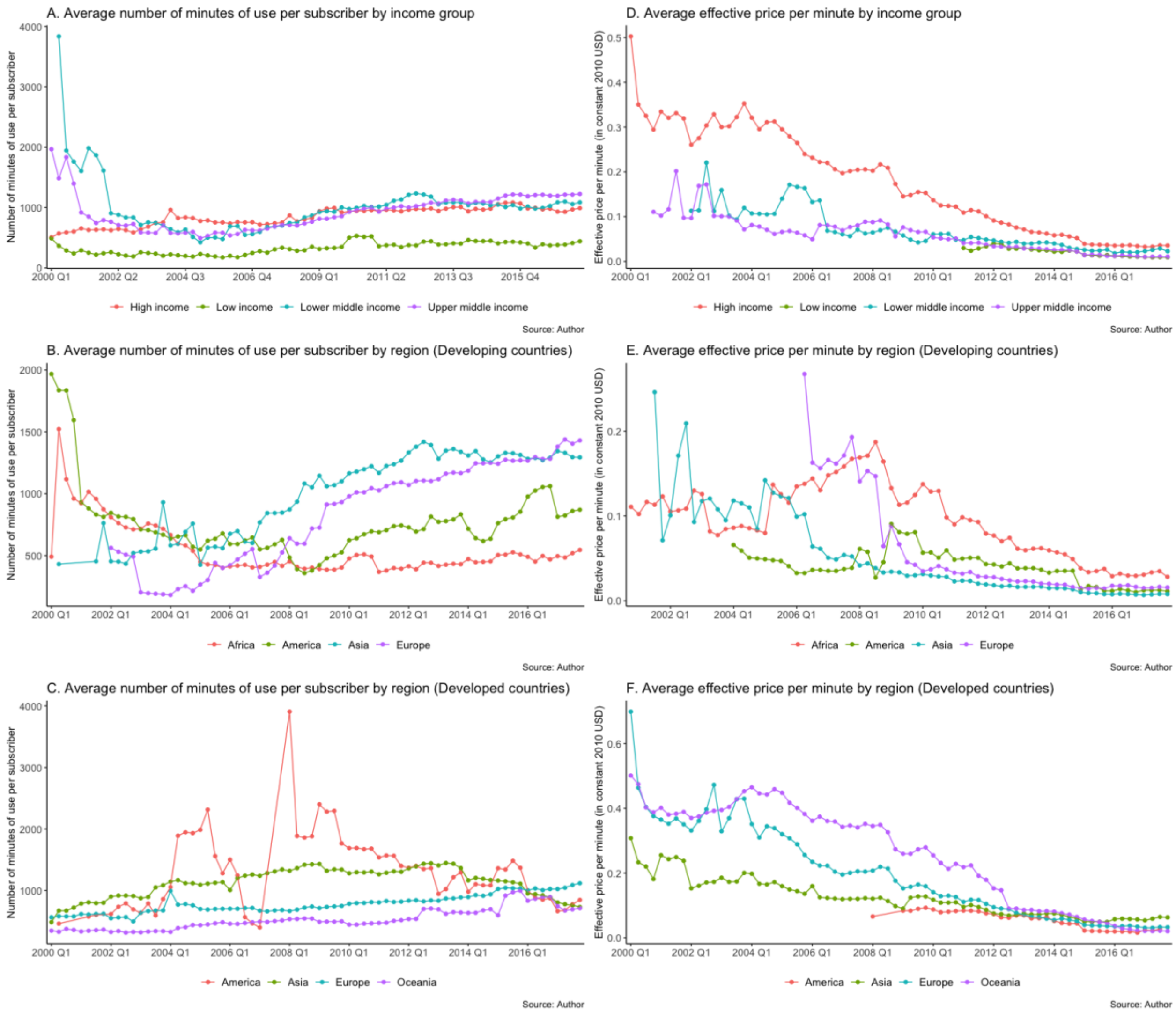

Figure 1: Average minutes of use and prices of a minute of call evolution

An immediate question from this observation is how demand for telecommunications services reacts to price changes. The answer depends on the estimation of the demand price elasticity, which is significant in terms of policy implications. Consider the example of a tax policy that led to a 20 percent increase in prices. With a demand price elasticity of -0.3, one could, ceteris paribus, assert that demand would decrease by 6 percent. Suppose that the elasticity was -1.1; then one would expect a decrease in demand of 22 percent, ceteris paribus. In this example, the first situation leads to a lower impact on consumers, while allowing the government to collect more revenues. It therefore serves as a reference, because it allows a prediction of the potential effects that a policy might have on the demand side. Furthermore, as previously explained, for Carlton and Perloff (2004) and Dewenter and Haucap

(2008), the demand price elasticity is an important indicator of companies' decision to engage in collusive behavior.

2. Literature review

Many studies have investigated the question of telecommunications services demand price elasticity in the economics literature and considered different markets. Some considered the fixed telephone market (Das and Srinivasan, 1999; Röller and Waverman, 2001; Martins, 2003), others the mobile telephony market (Madden et al., 2004; Lee and Lee, 2006; Dewenter and Haucap, 2008; Kathuria et al., 2009; Koutroumpis et al., 2011; Karacuka et al., 2011; Hausman and Ros, 2013; Hakim and Neaime, 2014), while others have looked into both markets (Waverman et al., 2005; Garbacz and Thompson, 2007; Caves, 2011). Concerning the type of data used, most studies considered panel or time series data at an aggregated country level to estimate price elasticities (Hausman and Ros, 2013; Garbacz and Thompson, 2007; Waverman et al., 2005). Some authors also used operator data at country level to analyze demand for telecommunications services (Koutroumpis et al., 2011; Dewenter and Haucap, 2008; Karacuka et al., 2011). Table A.5 in the appendix presents more detailed information on these studies.

Martins (2003), Madden et al. (2004), and Waverman et al. (2005) compared the price elasticity based on countries' income level and found that the demand was more elastic in developing countries. Lee and Lee (2006) incorporated competition in their analysis by comparing the demand price elasticity between pre-competition and post-competition periods and found that it decreased between the two periods. Kathuria et al. (2009) considered the market development level and compared the price elasticity between Indian states with low and high penetration. Their results showed that the states with low penetration faced higher demand price elasticity than those with high penetration. Dewenter and Haucap (2008) and Karacuka et al. (2011), considering operator data, compared the demand price elasticity between the mobile prepaid and postpaid markets in Austria and Turkey respectively: both studies concluded that the price elasticity was higher for the postpaid markets. Dewenter and Haucap (2008) also differentiate between the price elasticity in private and business usage. Hausman and Ros (2013) estimated the price elasticity to evaluate consumer welfare variation in Mexico, and suggested that regulatory authorities should avoid asymmetric regulation. However, they did not explicitly include operators' position or market shares in their analysis.

A novelty of my study is that the data allow me to consider the two types of data previously mentioned, i.e., data at operator level and data covering many countries, including developing and developed countries; this allows comparisons based on operator and market characteristics. Although Dewenter and Haucap (2008), Karacuka et al. (2011), and Hausman and Ros (2013) use a difference-GMM as an estimation strategy, I consider a system-GMM, which produces more efficient and consistent estimates than the difference-GMM, and is more suitable for unbalanced panel datasets. Unlike Kathuria et al. (2009), who use the median penetration rate to define the level of market development, I use Rogers's (1976) innovation diffusion theory to identify three levels of market development.[1] In addition, to complete Hausman and Ros's (2013) analysis, I investigate the potential difference in price elasticities based on operators' positions or market shares. Furthermore, in the studies enumerated in this section, Hausman and Ros's (2013) 2011 data are the most recent; since 2011, the sector has undergone significant changes. Therefore, my study constitutes an update of the existing literature on mobile voice communication demand.

III. Empirical strategy

To estimate mobile voice communication demand price elasticity, I draw on Houthakker and Taylor's (1970) model[2], which has been used in several studies, including Swamy (1968), Phlips (1971), and Sexauer (1977). The model is defined as follows:

$$ln(y_{ijt}) = \beta ln(y_{ijt-1}) + \delta ln(p_{ijt}) + \gamma X_{ijt} + \alpha_i + \eta_j + \theta_{ij} + \epsilon_{ijt} \quad (1)$$

where $ln(y_{ijt})$ is the logarithm of the total number of minutes of use per subscriber at a country-operator level over quarter t and represents the individual demand of a subscriber of operator i in country j during quarter t. $ln(p_{ijt})$ is the logarithm of the effective price of a minute of call, X_{ijt} is a vector of control variables, including the logarithm of the GDP per capita, the number of SIM cards per unique subscriber, and a time trend.[3] α_i, η_j, and θ_{ij} represent fixed effects, respectively, at the operator, country, and country-operator levels. ϵ_{ijt} is the error term. δ, which is the variable of interest, represents the short-run price elasticity, while the long-run price elasticity, ρ, is determined by the formula

$$\rho = \frac{\delta}{1-\beta} \quad (2)$$

[1] Indeed, innovation diffusion theory holds that the evolution of the penetration rate of an innovation in a given population follows an S-curve. Initially, the adoption rate of the innovation is low, particularly by innovators. Over time, the phenomenon of imitation leads to increasingly more people adopting the innovation, until the market reaches maturity.

[2] The Houthakker-Taylor model allows consideration of the relation between past and current consumptions and determines both short- and long-run elasticities. Indeed, the model postulates that current demand is not only determined by changes in price, income, or other variables, but also by consumers' habits (Houthakker and Taylor, 1970).

[3] In figure 1, there is an apparent trend in the individual demand; I therefore add a time trend to account for the autonomous structural changes in the demand. Houthakker and Taylor (1970) argue that there are two types of structural changes: autonomous change, which is not caused by preferences in demand and arises externally, and endogenous change, which is due to real time demand.

I use an unbalanced panel of firm level quarterly data from Q1 2000 to Q4 2017. The data come from the GSMA Intelligence database (GSMA, 2018), which covers 237 countries and territories and comprises market data (e.g., market shares, numbers of subscribers, market penetration, etc.), financial data (e.g., turnover, OPEX, CAPEX, and their decompositions, etc.), and communication volumes (e.g., outbound and inbound national and international minutes, SMSs, and data volumes).

As I have data on total minutes of use and the number of subscribers by operator in each country, I estimate the number of minutes of use by subscriber to obtain each operator's individual demand relative to their market share. To determine prices, I use total voice revenue data in constant 2010 USD and compute, for each operator, the average revenue per minute of use (this also applies to MB of data used).[4] Data on GDP per capita come from World Development Indicators. As the main variables are in quarterly frequency and GDP per capita in yearly format, I extrapolate quarterly GDP per capita linearly. An important issue in the telecommunications sector is the role of promotional offers, which affect demand structure significantly. In developing countries, a subscriber can have many SIM cards to benefit from these promotions.[5] Following Karacuka et al. (2011), I therefore consider the number of SIM cards per subscriber from GSMA Intelligence as a proxy for promotional offers. Since my interest is in elasticities, I use the logarithmic form of the number of minutes of use per subscriber, the price of a minute of use, and the GDP per capita, for the purpose of interpreting coefficients. Tables A.1–A.3 and A.4 in the appendix present the descriptive statistics and the data description, respectively.

To estimate price elasticity in the telecommunications sector, many authors have used panel fixed effects models. However, their models do not include a lagged dependent variable, as it leads to inconsistent estimates because of its correlation with the error term (Nickell, 1981). Therefore, a dynamic panel model is appropriate. In addition, endogeneity is an important issue when estimating a demand model, as price and demand are directly related.[6] Hausman and Ros (2013) and Dewenter and Haucap (2008) used a difference-GMM to estimate their dynamic panel model. The difference-GMM

[4] Voice revenues include both revenues from incoming, outgoing, and roaming minutes. Koutroumpis et al. (2011), Hausman and Ros (2013), Hakim and Neaime (2014), and Dewenter and Haucap (2008) also used this method to determine the price of a unit of communication. This, additionally, explains the use of total minutes of use rather than outbound minutes of use, for which I do not have data by operator. Furthermore, a subscriber's welfare is affected when he receives calls, which justifies the use of total voice traffic.

[5] These promotions generally involve the purchase of communications top-ups. Indeed, for a given top-up amount, a bonus of x percent, which can even go up to 200 percent or 400 percent, can be applied. However, in general, this credit bonus can only be used for on-net calls, which are also less expensive. This means that subscribers prefer a SIM card for each operator or several operators, to have more communication time with their contacts, who may be subscribers of different operators.

[6] Prices are considered endogenous because of the simultaneity problem that may occur with the demand for voice communication. Indeed, there are unobserved factors, such as regulation or supply forces in the telecommunications market, which affect both subscribers' demand and operators' pricing strategies; these factors are known to both groups (Hausman and Taylor, 1981; Hausman et al., 1994; Hausman and Leonard, 2002; Garbacz and Thompson, 2007; Dewenter and Haucap, 2008; and Hausman and Ros, 2013). Following Hausman and Ros (2013), I consider GDP per capita as an exogenous variable.

method overcomes these issues by eliminating the heterogeneity bias and mitigating endogeneity concerns. However, Blundell and Bond (1998) and Blundell et al. (2001) argue that it produces less efficient and consistent estimates than the system-GMM in the presence of time persistent variables; however, the stationarity condition must be verified. Nonetheless, Hauk and Wacziarg (2009) argue that the system-GMM produces reduced bias compared to the difference-GMM, even when the stationarity condition is not verified. Moreover, Roodman (2009) argues that, with unbalanced panel data, such as mine, the system-GMM is preferable because the difference-GMM has the shortcoming of amplifying gaps. The system-GMM entails estimating a system of equations with a levels-equation and a difference-equation in which the treatment of the endogenous variables is as follows: In the levels-equation, lagged first differences are used as instruments and, in the difference-equation, the lagged levels are considered as instruments, thus overcoming the issue of endogeneity. I therefore employ a two-step[7] system-GMM estimator (Blundell and Bond, 1998).

IV. Results

The results of the estimations are presented in Tables 1 to 6. To avoid a proliferation of instruments, I restrict and collapse the instruments matrix (Roodman, 2009). The Hansen J-test confirms the validity of the instruments. Additionally, I correct the finite sample bias by using Windmeijer (2005) standard errors. The AR(2) test p-value reveals an absence of second order correlation in the dependent variable. The coefficient of the lagged dependent variable is positive and statistically significant, and its high value supports the appropriateness of the system-GMM.

1. Main results

Column 1 of table 1 presents the main results for the global sample. The coefficient of lp, which represents the short-term price elasticity of voice communication demand, is -0.16 and significant at the 1 percent level. Notably, in the short-run, subscribers are less sensitive to price changes. The long-run price elasticity is estimated to be -0.85, and is significant at the 1 percent level.[8] A 10 percent increase in the effective price per minute would result in a decrease in the number of minutes of use per subscriber of 8.5 percent. The lgdp coefficient is equal to 0.46 in the long-run, and significant at the 1 percent level. The individual demand for voice communication increases by 4.6 percent for a GDP per capita increase of 10 percent. Promotional offers, measured by the number of SIM cards per unique subscriber, positively and significantly affect demand for voice communication.

[7] A two-step estimator is considered to produce estimates that are more robust to heteroscedasticity and other disturbances (see, e.g., Tsionas (2019)) than a one-step estimator. Dewenter and Haucap (2008) used a one-step difference GMM.
[8] I used the delta method to compute the standard errors (Greene, 2003).

As explained by Houthakker and Taylor (1970) and Dewenter and Haucap (2008), cross-price elasticities of other telecommunications services can play an important role in the demand estimation, as, for example, complementarity or substitutability can occur between internet data usage and voice communication. I therefore investigate the relation between voice communication and internet data usage by including the logarithm of the price of a megabyte (MB) of mobile internet data usage (lpd) to determine the cross-price elasticity.[9] A positive (negative) coefficient of the cross-price elasticity reveals a substitutability (complementarity) relation between voice communication and internet usage. Column 2 of table 1 presents the results. The coefficient of lpd is positive but not significant; therefore, the substitution effect for internet data usage and mobile voice communication is inconclusive. The long-term own price elasticity of voice communication remains significant at the 1 percent level and is equal to -0.79, which is comparable to the one estimated in column 1.

Due to differences in the terms of fixed line or other information and communication technology (ICT) infrastructure availability and regulation between developed and developing countries, I include in the estimations the proportion of households with a fixed line telephone (in column 3), the proportion with a computer (column 4), and the overall ICT regulatory environment score (column 5). The results remain robust to the control for these factors.

To explore the heterogeneity of the price elasticity between developed and developing countries, I consider the same specifications as in table 1 for each country group. Table 2 presents the results. The results for operators in developing countries are presented in columns 1 to 8. The short-run usage price elasticity is -0.19 and the long-run price elasticity is -0.82, statistically significant at the 5 percent and 1 percent levels, respectively. The lgdp coefficient, which represents the short-run (long-run) income elasticity of voice communication demand, is positive and significant at the 5 percent level, and equal to 0.07 (0.32). Additionally, promotional offers positively and significantly affect subscribers' demand for voice communication. The coefficient of lpd is positive, reflecting a substitution of internet data usage with voice communication; however, the coefficient is not significant. The long-run price elasticity remains stable in terms of coefficient (-0.77) and significance level. It remains robust to the control for fixed line and computers infrastructures, and regulation. Furthermore, in columns 6 to 8, I investigate the differences in price elasticities based on the income level of country of location. I therefore generate, for each country group, a dummy variable, lic, which takes on the value 1 for low income countries, and 0 otherwise. I repeat the process for low middle-

[9] I consider lpd only in this part of the results. Including it in the other regressions leads to a significant drop in the number of observations, since there are many missing data for the variable.

income and upper middle income countries, whose dummy variables are, respectively, lmi and umi. I then include, for each group, its dummy variable and its interaction with lp. A significant effect of the interaction term means that the concerned country group exhibits a different price elasticity compared to the other groups. The net effect is then obtained by adding the lp and interaction term coefficients. Clearly, none of the interaction terms is significant, suggesting no evidence of differential price elasticity due to the income level of country of location.

Columns 9 to 13 of table 2 present the results for operators in developed countries. In column 9, the short-run price elasticity is significant at the 1 percent level and is equal to -0.37. In the long-run, the price elasticity increases to -1.12, and this coefficient is significant at the 1 percent level. The short-run (long-run) income elasticity of demand is positive, significant at the 1 percent level, and equal to 0.16 (0.48). Furthermore, promotional offers positively affect subscribers' demand for voice communication; however, unlike the developing countries group, its coefficient is not significant. Notably, the price elasticity estimates for developed countries are higher than those for developing countries. This result contradicts, at this stage, the finding by Martins (2003).[10] Figure 2 presents some evidence that could justify this finding. Indeed, this could be due to an important substitute for mobile phones in terms of usage, which is the fixed line telephone in developed countries. Indeed, Waverman et al. (2005) argue that mobile phones tend to be substitutes for fixed lines in developing countries, but complements in developed countries in terms of access. Figure 2.C explains this assertion; as there are as many fixed line subscriptions as there are mobile phone subscriptions in developed countries, one can expect that, if the effective price of a mobile minute of call increases, subscribers should prefer using their fixed lines to using their mobile phones. In developing countries, this option is not available for a large proportion of mobile subscribers. Furthermore, one notes, in figure 2.A, that prepaid subscriptions outnumber contracts in both developed and developing countries. However, contract subscription is more advanced in developed countries than in developing countries (figure 2.D). Lambrecht and Skiera (2006) found that, with changes in prices, prepaid consumers were more likely to churn, and contract consumers were more likely to stay with the same operator but switch to another tariff. I argue that churning does not significantly affect the minutes of use per subscriber, as consumers churn to continue benefiting from the same services and demand, while switching to a lower tariff reduces the average individual demand. This may therefore explain the observation that operators in developed countries have higher demand price elasticity than those in developing

[10] However, Martins et al. (2003) executed their study on data before 2000. In sub-section 3 of the results section, I divide my sample into two sub-samples to see the evolution of the price elasticity, and thus compare my findings to those of other studies.

countries. Furthermore, Dewenter and Haucap (2008) and Karacuka et al. (2011) found that demand was more elastic in postpaid markets. It is worth noting that the development of internet services in developed countries could also explain the higher substitution effect with voice communication. In column 10, the coefficient of lpd is positive and statistically significant at the 5 percent level, suggesting that voice communication is a substitute for internet data usage in developed countries. The short-run price elasticity increases to -0.56, while the long-run price elasticity decreases to -0.82, and becomes comparable to the estimates for the global and developing countries sample. In columns 11 to 13, I control for fixed line and computers infrastructures, and regulation.[11] The estimates remain robust to these factors.

In the next subsection, I analyze the price elasticity of demand with respect to country of location market penetration level.

[11] In column 13, the results show that regulation negatively affects the demand for mobile voice communication. That could be explained by the fact that developed countries generally have strict regulatory policies, which tend to limit competition (Hausman et al., 1997; Vogelsang, 2017).

Table 1: Main results for the global sample

	(1)	(2)	(3)	(4)	(5)
L.lmns	0.810***	0.618***	0.812***	0.791***	0.838***
	(0.0528)	(0.1581)	(0.0801)	(0.0546)	(0.0539)
lp	-0.161***	-0.302**	-0.164*	-0.184***	-0.127**
	(0.0548)	(0.1357)	(0.0975)	(0.0536)	(0.0515)
lgdp	0.087***	0.156**	0.109	0.084***	0.071**
	(0.0307)	(0.0698)	(0.0726)	(0.0270)	(0.0289)
SIMpsubs	0.099**	0.035	0.109	0.122***	0.061*
	(0.0416)	(0.0602)	(0.0830)	(0.0447)	(0.0333)
time trend	-0.006***	-0.010**	-0.007	-0.008***	-0.005**
	(0.0023)	(0.0049)	(0.0050)	(0.0025)	(0.0023)
lpd		0.051			
		(0.0364)			
fixed			9.62e-5		
			(0.0007)		
computers				0.001	
				(0.0006)	
regulation					8.93e-5
					(0.0004)
Constant	1.108***	2.328**	0.968*	1.428***	0.962***
	(0.3202)	(1.1873)	(0.5577)	(0.4168)	(0.3363)
Observations	4339	966	1129	4236	3837
Groups	174	73	100	173	170
Instruments	27	28	30	30	30
AR1-pvalue	0.00	0.00	0.01	0.00	0.00
AR2-pvalue	0.82	0.57	0.30	0.80	0.82
Hansen-pvalue	0.13	0.51	0.28	0.23	0.15
LR price elasticity	-0.851***	-0.791***	-0.876***	-0.880***	-0.785***
Standard error	(0.1002)	(0.1210)	(0.2198)	(0.0856)	(0.1154)

Robust standard errors in brackets. *p<0.10, **p<0.05, and ***p<0.01. The lp is considered endogenous, while the other variables are considered exogenous.

Table 2: Main results for developing and developed countries

	Developing countries								Developed countries				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
L.lmns	0.768***	0.663***	0.712***	0.758***	0.820***	0.752***	0.781***	0.789***	0.667***	0.316*	0.890***	0.666***	0.662***
	(0.0864)	(0.1542)	(0.1367)	(0.0911)	(0.0719)	(0.0900)	(0.0879)	(0.0826)	(0.0703)	(0.1682)	(0.0329)	(0.0722)	(0.0757)
lp	-0.189**	-0.260*	-0.248*	-0.199**	-0.129*	-0.204**	-0.182**	-0.152**	-0.374***	-0.557***	-0.121**	-0.375***	-0.373***
	(0.0855)	(0.1363)	(0.1432)	(0.0896)	(0.0696)	(0.0857)	(0.0865)	(0.0734)	(0.0774)	(0.1325)	(0.0515)	(0.0788)	(0.0740)
lgdp	0.075**	0.106**	0.145	0.077**	0.053**	0.083**	0.053	0.036	0.161***	0.178**	-0.026	0.162***	0.156***
	(0.0330)	(0.0514)	(0.0887)	(0.0390)	(0.0263)	(0.0338)	(0.0334)	(0.0399)	(0.0540)	(0.0693)	(0.0432)	(0.0568)	(0.0448)
SIMpsubs	0.155*	0.031	0.174	0.165*	0.092	0.172*	0.131*	0.132*	0.106	0.510*	-0.049	0.102	0.038
	(0.0839)	(0.0669)	(0.1197)	(0.0882)	(0.0646)	(0.0880)	(0.0788)	(0.0792)	(0.0730)	(0.2685)	(0.0451)	(0.0796)	(0.0502)
time trend	-0.008**	-0.011**	-0.012	-0.009**	-0.006*	-0.009**	-0.007**	-0.007**	-0.012***	0.004	-0.001	-0.012***	-0.011***
	(0.0038)	(0.0054)	(0.0074)	(0.0039)	(0.0034)	(0.0037)	(0.0032)	(0.0030)	(0.0029)	(0.0101)	(0.0029)	(0.0030)	(0.0023)
lpd		0.037								0.207**			
		(0.0376)								(0.0857)			
fixed			-0.001								0.002		
			(0.0013)								(0.0012)		
computers				2.523e-4								-1.169e-4	
				(0.0007)								(0.0017)	
regulation					0.001								-0.003***
					(0.0007)								(0.0011)
lp.lic						-0.070							
						(0.0553)							
lic						-0.286							
						(0.2331)							
lp.lmi							0.028						
							(0.0364)						
lmi							0.074						
							(0.1390)						
lp.umi								-0.021					
								(0.0346)					
umi								-0.013					
								(0.1333)					
Constant	1.671***	2.759**	1.927*	1.826***	1.296**	1.783***	1.702**	1.761**	1.992***	0.305	0.802	2.008***	2.268***
	(0.6275)	(1.3667)	(1.0323)	(0.6736)	(0.5582)	(0.6402)	(0.6673)	(0.7107)	(0.4825)	(2.8887)	(0.5541)	(0.5275)	(0.4919)
Observations	2182	722	760	2103	2059	2182	2182	2182	2157	244	369	2133	1778
Groups	92	51	57	91	91	92	92	92	82	22	43	82	79
Instruments	27	28	28	28	28	51	51	51	33	20	34	34	34
AR1-pvalue	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.00
AR2-pvalue	0.20	0.51	0.17	0.20	0.30	0.18	0.23	0.23	0.10	0.42	0.12	0.10	0.15
Hansen-pvalue	0.30	0.57	0.15	0.30	0.44	0.99	0.16	0.23	0.18	0.78	0.18	0.17	0.13
LR price elasticity	-0.817***	-0.769***	-0.859***	-0.820***	-0.717***	-0.821***	-0.831***	-0.724***	-1.122***	-0.815***	-1.099***	-1.123***	-1.104***
Standard error	(0.1153)	(0.1412)	(0.2111)	(0.1170)	(0.1419)	(0.1098)	(0.1799)	(0.1446)	(0.1440)	(0.1150)	(0.3149)	(0.1464)	(0.1105)

Robust standard errors in brackets. *p<0.10, **p<0.05, and ***p<0.01. The lp and interactions terms are considered endogenous, while the other variables are considered exogenous.

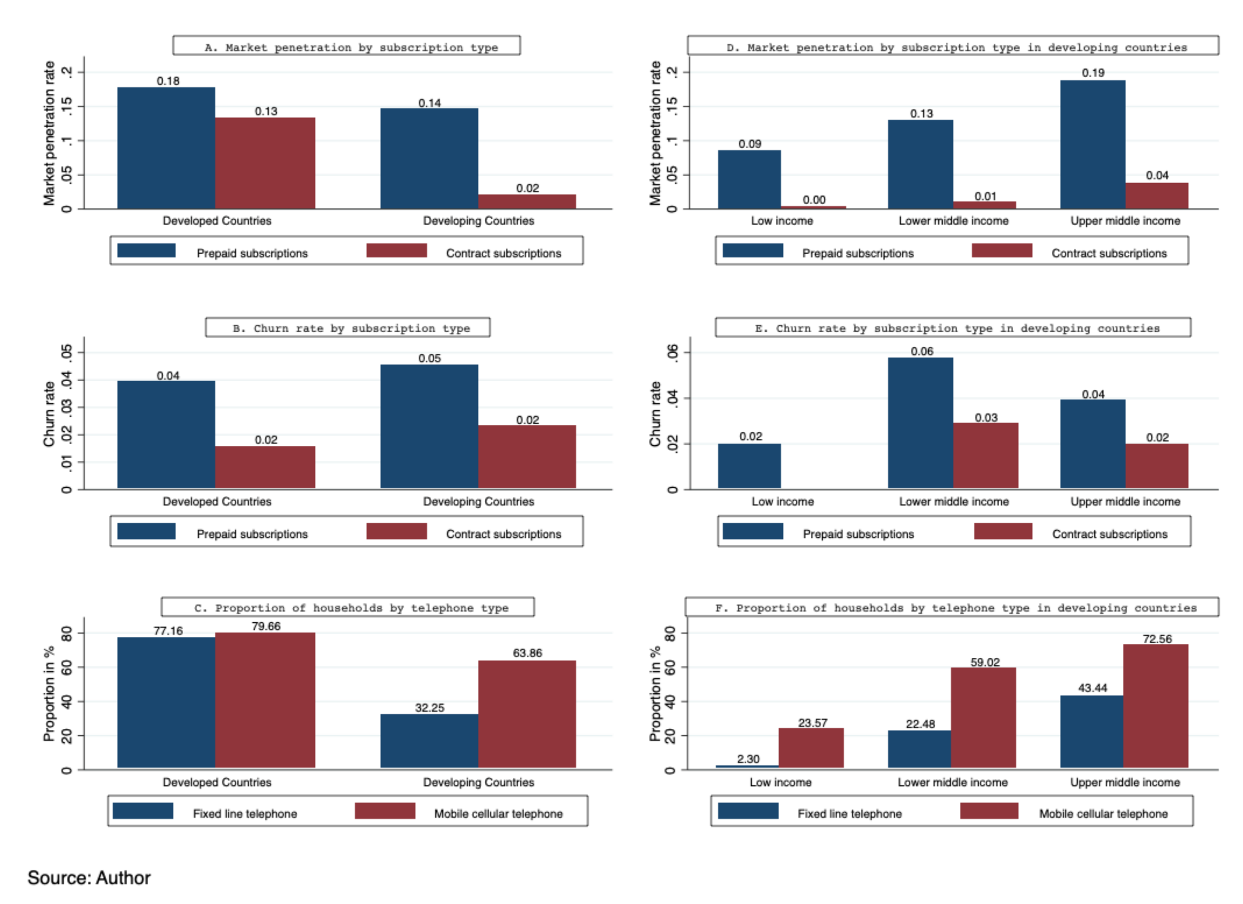

Figure 2: Comparison of some market characteristics by income level

2. Country of location market penetration level

In this section, I examine whether price elasticity depends on country market penetration level. I therefore divide the sample into 3 sub-samples, following the innovation diffusion theory. The first sub-sample, for countries with a market penetration lower than 35 percent, is classified as one of low penetration. The second group is for countries with a market penetration between 35 percent and 64 percent, which is classified as one of growth. The last group includes countries with a market penetration higher than 64 percent that I consider as mature. I then estimate the model for each sub-sample.

I first consider the whole sample, including both developing and developed countries (columns 1 and 2 of table 3).[12] The results for operators in the growing markets are presented in column 1. The short-run price elasticity is -0.07 but not significant; the long-run price elasticity is -0.57 and significant

[12] I only consider the markets in the growth and mature classes, as there is no low penetration market in the developed countries group.

at the 10 percent level. Regarding operators in the mature markets (column 2), the short-run price elasticity is -0.16 and significant at the 1 percent level, while the long-run price elasticity is significant at the 1 percent level and equal to -0.86.

Columns 5 to 7 of table 3 present the results for operators in the developing countries. For operators in the less penetrated countries group (column 5), I find a short-run price elasticity of -0.48 and a long-run price elasticity of -1.17, which are statistically significant at the 5 percent and 1 percent levels, respectively. For operators in the growing markets (column 6), the short-run price elasticity is -0.16, while the long-run price elasticity is -0.73; only the long-run price elasticity is statistically significant at the 1 percent level. For operators in the mature markets, the short-run price elasticity is -0.13, whereas the long-run price elasticity is -0.61, which is significant at the 1 percent level (column 7). I note that the short-run price elasticity is not significant, which suggests that price changes do not affect subscribers' demand for voice communication in the short-run in the growing and mature developing markets. Consistent with Martins (2003) and Kathuria et al. (2009), the results for the developing countries support the underlying assumptions in demand theory, i.e., that demand price elasticity is higher in smaller markets, where the diffusion process begins, and whose elasticity decreases with the development of the diffusion process. Figures 3.A, 3.B, and 3.C show some evidence of these findings. Indeed, as there are more prepaid subscriptions than contracts, one expects that, as previously explained, price changes will lead to more churn than switching, and this increases with the level of market development. Furthermore, the proportion of households with fixed line telephones increases with market penetration level, offering potential for substitution.

The results for the developed countries are presented in Columns 8 and 9 of table 3. For operators in the growing markets (column 8), the short-run price elasticity is -0.38 and the long-run price elasticity is -0.84, which are both statistically significant at the 1 percent level. For operators in the mature markets, the short-run price elasticity is -0.33, while the long-run price elasticity is -1.09; they are also both significant at the 1 percent level (column 9). I therefore conclude that, in the developed countries, price elasticity increases with market development level. In figure 3.D, operators in the markets with high penetration have more contract subscriptions, which suggests that the subscribers in this market are more likely to switch than those in the growing markets. In addition, figure 3.F shows that, in the growing developed market, some fixed line telephone subscribers do not have mobile phones, while all fixed line telephone subscribers are mobile subscribers in the highly penetrated markets. This suggests that subscribers in the developed markets with high penetration may be more likely to substitute mobile voice communication with fixed lines than those in the growing markets.

To test these arguments for validity, I include, in the global sample model specification, the ratio of contract to prepaid subscriptions (cont_prep), the ratio of fixed to mobile lines (fixe_mobile), and their interactions with lp (lp.cont_prep and lp.fixe_mobile) in columns 3 and 4 of table 3, respectively. The results show that the lp.cont_prep and lp.fixe_mobile coefficients are negative and significant at the 10 percent and 1 percent levels, respectively, supporting the explanation that countries with more contract subscriptions and more fixed line infrastructures experience greater price elasticity.

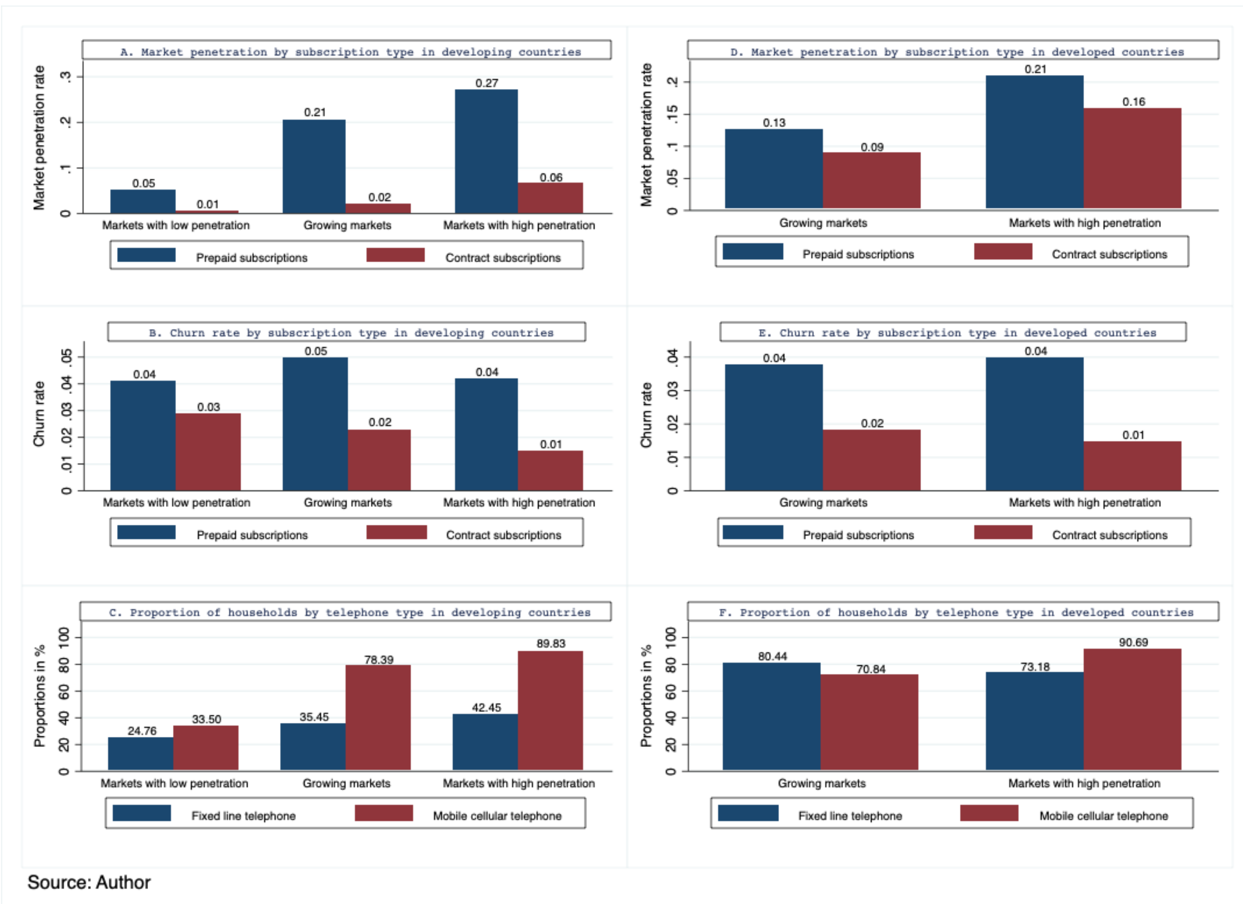

Figure 3: Comparison of some market characteristics by market penetration level

Table 3: Results by market penetration level

	Global sample				Developing countries			Developed countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.lmns	0.870***	0.816***	0.834***	0.754***	0.586***	0.782***	0.789***	0.543***	0.697***
	(0.0654)	(0.0503)	(0.0465)	(0.1015)	(0.1618)	(0.1428)	(0.0964)	(0.1336)	(0.0681)
lp	-0.074	-0.158***	-0.126**	-0.161*	-0.483**	-0.159	-0.128	-0.383***	-0.330***
	(0.0736)	(0.0469)	(0.0496)	(0.0905)	(0.2149)	(0.1524)	(0.0795)	(0.1474)	(0.0747)
lgdp	0.034	0.090***	0.066**	0.221***	0.137	0.066	0.053	0.169	0.133***
	(0.0300)	(0.0322)	(0.0277)	(0.0778)	(0.1247)	(0.0508)	(0.0445)	(0.1051)	(0.0482)
SIMpsubs	0.039	0.032	0.078**	0.116	0.236	0.127	0.026	-0.112	0.046
	(0.0612)	(0.0312)	(0.0320)	(0.1105)	(0.2730)	(0.1521)	(0.0513)	(0.1270)	(0.0628)
time trend	-0.002	-0.007***	-0.005**	-0.021***	-0.026***	-0.006	-0.007	0.003	-0.011***
	(0.0033)	(0.0020)	(0.0020)	(0.0062)	(0.0099)	(0.0062)	(0.0040)	(0.0028)	(0.0028)
cont_prep			-1.98e-5						
			(1.69e-5)						
lp.cont_prep			-1.46e-5*						
			(7.85e-6)						
fixe_mobile				-0.941***					
				(0.3561)					
lp.fixe_mobile				-0.213**					
				(0.1041)					
Constant	0.684	1.216***	1.046***	3.333***	4.580***	1.306	1.862**	0.182	2.118***
	(0.5219)	(0.3248)	(0.2862)	(0.8931)	(1.7107)	(1.0151)	(0.9030)	(0.6987)	(0.5064)
Observations	1487	2593	4318	898	259	1194	729	293	1864
Groups	105	126	173	95	28	75	47	30	79
Instruments	27	27	51	42	27	27	27	29	33
AR1-pvalue	0.00	0.00	0.00	0.01	0.07	0.00	0.00	0.07	0.00
AR2-pvalue	0.05	0.12	0.91	0.06	0.72	0.04	0.43	0.43	0.03
Hansen-pvalue	0.19	0.02	0.11	1.00	0.62	0.23	0.28	0.97	0.35
LR price elasticity	-0.569*	-0.856***	-0.762***	-1.524***	-1.166***	-0.728***	-0.610***	-0.838***	-1.089***
Standard error	(0.3123)	(0.1218)	(0.1242)	(0.1982)	(0.1870)	(0.2521)	(0.1892)	(0.1234)	(0.1475)

Robust standard errors in brackets. *p<0.10, **p<0.05, and ***p<0.01. The lp and interaction terms are considered endogenous, whereas the other variables are considered exogenous.

3. Time period

As shown in figure 1, the price of a minute of voice communication decreased over the years and was relatively constant for the period 2008–2009. At the beginning of the 2000s, telecommunications goods, such as telephones, were considered to be luxury goods due to their high cost of ownership. Therefore, only certain classes of people could buy and own mobile phones and obtain subscription during this period. Public main line telephones were the only way for less rich people to communicate, and prices were an important factor in the decision to call and the number of minutes of communication to use. Therefore, I expect that, in this time period, a change in price would result in a bigger change in consumers' choices. However, with time and the development of technologies, the cost of mobile phones has decreased, and the promotion of regulation in many countries contributes to more affordable telecommunications services, thus increasing the number of subscribers. The important role of telecommunications in people's lives and economic activities has led to a dependence on these services. I therefore consider the evolution of price elasticity over two periods, 2000–2008 and 2009–2017. Column 1 of table 4 presents the results for the first period for the global sample. The short-run price elasticity is significant at the 5 percent level and equal to -0.34. The long-run price elasticity is -1.21 and significant at the 1 percent level. Regarding the second period (column 2), the short-run price elasticity is significant at the 10 percent level and is estimated to be -0.07, while the long-run price elasticity is -0.59 and significant at the 1 percent level. Consistent with Lee and Lee (2006), I find that the price elasticity has decreased considerably over time.

For operators in the developing countries, the results are presented in columns 3 and 4 of table 4. Over the first period, the short-run price elasticity is -0.34, while the long-run price elasticity is -1.35. These estimates are significant at the levels of 10 percent and 1 percent, respectively (column 3). For the second period, the short-run price elasticity decreases to -0.06 but is not significant, whereas the long-run price elasticity is -0.50 and significant at the 5 percent level (column 4). Over time, in the developing countries, mobile services are assuming an important role in subscribers' lives' and decreasing their sensitivity to voice communication price changes.

The results for the developed countries are presented in columns 5 and 6 of table 4. Over the first period, the short-run price elasticity is -0.56 and the long-run price elasticity is -1.18. These estimates are both significant at the level of 1 percent (column 5). For the second period, the short-run price elasticity is -0.35 and the long-run price elasticity is -1.17 (column 6), both significant at the 1 percent level. Over the two time periods, the voice communication price elasticity remained constant.

As most of the studies on telecommunications services price elasticity use pre-2009 data, I compare my findings on the first period to theirs. I find support for the conclusion by Martins (2003) and Madden et al. (2004) that demand is more elastic in developing countries. Furthermore, consistent with Röller and Waverman (2001), Martins (2003), Waverman et al. (2005), Kathuria et al. (2009), Koutroumpis et al. (2011), Caves (2011), and Hakim and Neaime (2014), I find that the demand price elasticity is lower than -1.

Table 4: Results by time period

	Global sample		Developing countries		Developed countries	
	(1)	(2)	(3)	(4)	(5)	(6)
L.lmns	0.723***	0.889***	0.746***	0.874***	0.527***	0.705***
	(0.1091)	(0.0431)	(0.1230)	(0.0705)	(0.1270)	(0.0520)
lp	-0.336**	-0.065*	-0.343*	-0.063	-0.560***	-0.345***
	(0.1374)	(0.0387)	(0.1806)	(0.0621)	(0.1540)	(0.0579)
lgdp	0.181**	0.034	0.103	0.026	0.217**	0.126***
	(0.0787)	(0.0216)	(0.0808)	(0.0234)	(0.0926)	(0.0367)
SIMpsubs	0.186	0.027	0.516	0.036	0.024	0.036
	(0.1550)	(0.0205)	(0.3408)	(0.0427)	(0.1346)	(0.0451)
time trend	-0.009	-0.003	-0.022	-0.002	-0.002	-0.013***
	(0.0057)	(0.0016)	(0.0133)	(0.0026)	(0.0033)	(0.0024)
Constant	0.781	0.731***	3.096	0.876*	0.272	2.514***
	(0.5962)	(0.2780)	(1.9960)	(0.5158)	(0.6207)	(0.4677)
Observations	877	3462	261	1921	616	1541
Groups	70	160	28	83	42	77
Instruments	27	27	27	27	33	33
AR1-pvalue	0.01	0.00	0.04	0.00	0.05	0.00
AR2-pvalue	0.66	0.29	0.85	0.05	0.71	0.12
Hansen-pvalue	0.13	0.14	0.89	0.26	0.17	0.20
LR price elasticity	-1.213***	-0.585***	-1.351***	-0.500**	-1.183***	-1.171***
Standard error	0.1472	0.1556	(0.2230)	(0.2369)	(0.1560)	(0.1098)

Robust standard errors in brackets. *p<0.10, **p<0.05, and ***p<0.01. The lp is considered endogenous, while the other variables are considered exogenous.

4. Operators position and market share

In columns 1 and 4 of table 5, I investigate whether price elasticity differs between incumbent operators and followers, in both the developing and developed countries. I therefore generate a dummy variable, "incumbent", taking on a value of 1 for each quarter and country if the operator is an incumbent, and 0 otherwise. For operators in developing and developed countries, I find that the interaction term for lp and incumbent is negative but not significant, suggesting that price elasticity does not vary between incumbent operators and followers in both samples.[13] The long-run price elasticity estimates remain robust and equal to -0.82 for operators in the developing countries (column 1) and -1.13 for those in the developed countries (column 4), respectively. The two coefficients are significant at the 1 percent level. Furthermore, I examine whether operators' market shares are a factor in estimating the price elasticity. I divide the operators into two groups for the developing and developed countries. Using the market share of 0.27[14] as a reference, I distinguish

[13] However, Dewenter and Haucap (2008) find that price elasticity is higher for incumbent operators in Austria.
[14] I consider the median as the reference market share.

between operators with low market shares and those with high market shares.

Columns 2 and 3 of table 5 present the results for the low and high market share groups, respectively, in developing countries. For the operators with low market shares (column 2), I find that the short-run price elasticity is -0.23 and statistically significant (at the 5 percent level), while the long-run price elasticity is -0.80 and statistically significant (at the 1 percent level). For the operators with high market shares (column 3), the short-run price elasticity is -0.24 and the long-run price elasticity is -0.85, which are statistically significant at the 5 percent and 1 percent levels, respectively.

Columns 5 and 6 of table 5 present the results for the low and high market share groups, respectively, in developed countries. For the operators with low market shares (column 5), the short-run price elasticity is -0.45 and significant at the 1 percent level, while the long-run price elasticity is estimated to be -1.24 and is statistically significant at the 1 percent level. For the operators with high market shares (column 6), the short-run price elasticity is -0.47 while the long-run price elasticity is -1.20, which are both statistically significant at the 1 percent level.

The results corroborate my previous finding that price elasticity does not vary with operators' market position in both developing and developed countries.

Table 5: Results by operators' characteristics

	Developing countries			Developed countries		
	(1)	(2)	(3)	(4)	(5)	(6)
L.lmns	0.761***	0.713***	0.719***	0.679***	0.635***	0.607***
	(0.0905)	(0.1217)	(0.0951)	(0.0671)	(0.1305)	(0.0757)
lp	-0.196**	-0.230**	-0.240**	-0.362***	-0.450***	-0.470***
	(0.0880)	(0.1136)	(0.1087)	(0.0769)	(0.1476)	(0.0898)
lgdp	0.078**	0.095**	0.092**	0.151***	0.269***	0.193***
	(0.0343)	(0.0372)	(0.0363)	(0.0515)	(0.0695)	(0.0665)
SIMpsubs	0.164*	0.166**	0.209*	0.101	0.100	0.125
	(0.0883)	(0.0747)	(0.1140)	(0.0693)	(0.0787)	(0.0882)
time trend	-0.008**	-0.011**	-0.009**	-0.012***	-0.017***	-0.015***
	(0.0038)	(0.0052)	(0.0048)	(0.0029)	(0.0044)	(0.0036)
lp.incumbent	-0.077			-1.138		
	(0.5070)			(3.5185)		
incumbent	-0.204			-1.719		
	(1.8510)			(5.9953)		
Constant	1.712***	2.211**	1.863**	1.954***	1.789**	2.330***
	(0.6424)	(1.0581)	(0.7494)	(0.4787)	(0.7891)	(0.5433)
Observations	2182	707	1475	2157	483	1674
Groups	92	39	60	82	34	63
Instruments	34	28	26	46	33	33
AR1-pvalue	0.00	0.00	0.00	0.00	0.08	0.00
AR2-pvalue	0.18	0.03	0.68	0.09	0.11	0.95
Hansen-pvalue	0.56	0.40	0.34	0.72	0.35	0.11
LR price elasticity	-0.819***	-0.802***	-0.852***	-1.126***	-1.235***	-1.196***
Standard error	(0.1146)	(0.1867)	(0.1315)	(0.1454)	(0.1764)	(0.1486)

Robust standard errors in brackets. *p<0.10, **p<0.05, ***p<0.01. The lp and interaction term are considered endogenous, whereas the other variables are considered exogenous.

5. Region of location

In table 6, I examine the differences in price elasticities based on operators' country of location region. I therefore generate, for each country group, a dummy variable, Africa (similarly for America, Asia, Europe, and Oceania[15]), which takes on the value 1 for African countries (similarly for American, Asian, European, and Oceania countries), and 0 otherwise. I then include, for each group, its dummy variable and its interaction with lp. A significant effect of the interaction term means that the concerned countries group exhibits differential price elasticity compared to the other groups.

The results for the developing countries are presented in columns 1 to 4 of table 6. They show that only the lp.Europe and lp.Asia coefficients are statistically significant at the level of 5 percent and 1 percent, respectively. The coefficient of lp.Europe is negative, indicating that operators in developing European countries experience higher price elasticity than those in other developing countries. For

[15] Oceania is missing from the developing countries sample, as is Africa from the developed countries sample.

these operators' region, the short-run (long-run) price elasticity is -0.24[16] (-1.09) and is statistically significant at the 5 percent level (1 percent level). This result may be explained by the fact that this region has more mobile contract subscriptions, more fixed line telephones, and a deeper internet market penetration than other developing countries. For lp.Asia, the coefficient is positive, indicating that operators in developing Asian countries experience lower price elasticity than those in other developing countries. The short-run (long-run) price elasticity for this region is estimated to be -0.13 (-0.52) and is significant at the 5 percent level (1 percent level). This may be explained by the increased adoption of mobile virtual networks, which allows operators to set lower prices. Demand for better quality of communication services has also significantly increased investment in the region, which produces a significant evolution of the mobile industry in the region. Furthermore, Asian telecommunication industries, such as those in China, Japan, and South Korea, have become significant players in the industry.[17] The long-run price elasticity is significant at the 1 percent level and, respectively, is equal to -0.86 and -0.63 for operators in Africa and America.

The results for the developed countries are presented in columns 5 to 8 of table 6. None of the terms for the interaction between the regional dummy variables and lp is significant, suggesting that, in developed countries, there is no evidence of price elasticity variation driven by operators' region. The long-run price elasticity estimate is significant at the 1 percent level and is, respectively, -1.32, -1.13, -1.16, and -1.06 for operators in the developed European, American, Asian, and Oceanian countries.

[16] This estimate is obtained by adding the coefficient of lp.Europe to that of lp (-0.163-0.082=-0.245).
[17] https://www-statista-com.ezproxy.uca.fr/topics/5748/telecommunications-industry-in-asia-pacific/.

Table 6: Results by operators' region of location

	Developing countries				Developed countries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.lmns	0.783***	0.776***	0.823***	0.743***	0.612***	0.640***	0.658***	0.685***
	(0.0719)	(0.0889)	(0.0724)	(0.0713)	(0.0600)	(0.0682)	(0.0681)	(0.0666)
lp	-0.187**	-0.163**	-0.111*	-0.239***	-0.512***	-0.407***	-0.397***	-0.334***
	(0.0753)	(0.0828)	(0.0591)	(0.0753)	(0.0722)	(0.0836)	(0.0716)	(0.0678)
lgdp	0.094**	0.067**	0.057**	0.069***	0.180***	0.173***	0.156***	0.146***
	(0.0418)	(0.0328)	(0.0273)	(0.0249)	(0.0492)	(0.0575)	(0.0518)	(0.0454)
time trend	-0.009***	-0.008**	-0.006**	-0.008***	-0.015***	-0.013***	-0.013***	-0.010***
	(0.0032)	(0.0039)	(0.0025)	(0.0026)	(0.0026)	(0.0031)	(0.0027)	(0.0024)
SIMpsubs	0.126*	0.154*	0.090*	0.175**	0.119*	0.130*	0.066	0.072
	(0.0708)	(0.0895)	(0.0529)	(0.0759)	(0.0649)	(0.0694)	(0.0705)	(0.0607)
lp.Africa	0.046							
	(0.0516)							
Africa	0.261							
	(0.1860)							
lp.Europe		-0.082**			0.070			
		(0.0391)			(0.0504)			
Europe		-0.330*			0.125			
		(0.1687)			(0.1128)			
lp.America			-0.046			-0.035		
			(0.0427)			(0.0734)		
America			-0.208			-0.005		
			(0.1539)			(0.2062)		
lp.Asia				0.105***			-0.086	
				(0.0384)			(0.0903)	
Asia				0.376**			-0.176	
				(0.1490)			(0.2211)	
lp.Oceania								0.064
								(0.0937)
Oceania								0.019
								(0.1482)
Constant	1.606***	1.730**	1.325***	1.693***	2.500***	2.197***	2.354***	1.758***
	(0.4620)	(0.6816)	(0.4843)	(0.4644)	(0.4602)	(0.4958)	(0.4665)	(0.4126)
Observations	2182	2182	2182	2182	2157	2157	2157	2157
Groups	92	92	92	92	82	82	82	82
Instruments	51	51	51	51	63	63	63	63
AR1-pvalue	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR2-pvalue	0.19	0.22	0.28	0.25	0.34	0.19	0.16	0.05
Hansen-pvalue	0.12	0.65	0.67	0.34	0.39	0.93	0.92	0.99
LR price elasticity	-0.862***	-1.092***	-0.627***	-0.522***	-1.320***	-1.131***	-1.161***	-1.061***
Standard error	(0.1537)	(0.1969)	(0.1300)	(0.1550)	(0.1281)	(0.1370)	(0.1147)	(0.1427)

Robust standard errors in brackets. *p<0.10, **p<0.05, and ***p<0.01. The lp and interaction terms are considered endogenous, whereas the other variables are considered exogenous.

V. Conclusion

I analyze mobile voice communication demand price elasticity in developing and developed countries using a dynamic panel model with quarterly operator data. I find that the short-run demand price elasticity is -0.19 (-0.37) for operators in developing (developed) countries, while, for the same operators, the long-run price elasticity is -0.82 (-1.12). Controlling for cross-price elasticity with internet data usage prices reveals that voice communication is a substitute for internet data usage in developed countries. Any shock in internet data usage would thus be reflected in the demand for voice communication in these countries. Across operators in developing countries, I find that those in Asia (Europe) have a lower (higher) long-term price elasticity than the other operators. Furthermore, in developing countries, the telecommunications services price elasticity has decreased over time, and operators in markets with low penetration experience a higher price elasticity than those in more deeply penetrated markets. However, in developed countries, the price elasticity has not changed significantly over the years, and increases with market development level. In addition, for both country groups, I find no evidence of differential price elasticity between incumbents and followers.

As pointed out by Qiang and Pitt (2003), Li et al. (2005), and Howard and Mazaheri (2009), reforms in regulatory policies for the telecommunications sector have a considerable impact on economies. My results have important implications in terms both of regulatory and tax policies. Indeed, in most developing countries, the texts setting out telecommunications regulatory frameworks date from the time of sector liberalization, i.e., before 2007, approximately. However, as pointed out by Biglaiser and Riordan (2000) and Jeanjean (2015), the sector has undergone many developments in terms of structure, technological progress and the development of new generations of technologies. My results, therefore, highlight the need for these countries to update their regulatory frameworks in line with the development of the sector. Furthermore, as mentioned by Klemm and Van Parys (2012), some policies are adopted in some countries by mimicking other countries that have implemented them. This is specifically the case in terms of tax policies.[18] Thus, finding different price elasticities based on different factors challenges the relevance of adopting policies that simply replicate those in other countries; important economic factors, such as income level and market development level or characteristics, must be considered. The high estimated price elasticities suggest that operators do not have an obvious interest in engaging in collusive behavior that would hinder competition. Moreover, the lack of evidence for a price elasticity differential driven by operators' position or market share supports the recommendations by Hausman and Ros (2013), who suggested that regulation should not

[18] In Africa for example, there is a great similarity in the tax systems applied to mobile network operators (Rota-Graziosi and Sawadogo, 2020).

be asymmetric on the dominant operator.[19]

Acknowledgements

I am thankful to Gregoire Rota-Graziosi, Tarna Hamid Silue, and Abdoul-Akim Wandaogo for their helpful discussions and comments. This work was supported by the Agence Nationale de la Recherche of the French government through the program "Investissements d'avenir" ANR-10-LABX-14-01. The usual disclaimers apply.

[19] The asymmetry in regulation refers to the application of a differentiated regulatory policy for dominant operators and other operators.

References

- Biglaiser, G., & Riordan, M. (2000). Dynamics of price regulation. *RAND Journal of Economics*, 744-767.
- Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1):115–143.
- Blundell, R., Bond, S., and Windmeijer, F. (2001). Estimation in dynamic panel data models: improving on the performance of the standard gmm estimator. In *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, pages 53–91. Emerald Group Publishing Limited.
- Carlton, D.W. and J.M. Perloff, 2004, *Modern Industrial Organisation*, 4th edition, Addison Wesley.
- Caves, K. W. (2011). Quantifying price-driven wireless substitution in telephony. *Telecommunications Policy*, 35(11):984–998.
- Das, P. and Srinivasan, P. V. (1999). Demand for telephone usage in India. *Information Economics and Policy*, 11(2):177–194.
- Dewenter, R. and Haucap, J. (2008). Demand elasticities for mobile telecommunications in Austria. *Jahrbücher für Nationalökonomie und Statistik*, *228*(1), 49-63.
- Garbacz, C. and Thompson, H. G. (2007). Demand for telecommunication services in developing countries. *Telecommunications Policy*, 31(5):276–289.
- Greene, W. (2003). Econometric analysis. 5th edn, ed. banister, r.
- GSMA (2018). Gsma intelligence database. Data retrieved from GSMA Intelligence, https://www.gsmaintelligence.com/data/.
- Hakim, S. and Neaime, S. (2014). The demand elasticity of mobile telephones in the Middle East and North Africa. *Research in International Business and Finance*, 32:1–14.
- Hauk, W. R. and Wacziarg, R. (2009). A monte carlo study of growth regressions. *Journal of Economic Growth*, 14(2):103–147.
- Hausman, J., Leonard, G., and Zona, J. D. (1994). Competitive analysis with differenciated products. *Annales d'Economie et de Statistique*, (34):159–180.
- Hausman, J. A. and Leonard, G. K. (2002). The competitive effects of a new product introduction: A case study. *The Journal of Industrial Economics*, 50(3):237–263.
- Hausman, J. A., Pakes, A., & Rosston, G. L. (1997). Valuing the effect of regulation on new services in telecommunications. *Brookings papers on economic activity. Microeconomics, 1997*, 1-54.
- Hausman, J. A. and Ros, A. J. (2013). An econometric assessment of telecommunications prices

and consumer surplus in Mexico using panel data. *Journal of Regulatory Economics*, 43(3):284–304.

- Hausman, J. A. and Taylor, W. E. (1981). Panel data and unobservable individual effects. *Econometrica: Journal of the Econometric Society*, pages 1377–1398.
- Houthakker, H. S. and Taylor, L. D. (1970). Consumer demand in the united states.
- Howard, P. N. and Mazaheri, N. (2009). Telecommunications reform, internet use and mobile phone adoption in the developing world. *World Development*, 37(7):1159–1169.
- Klemm, A., & Van Parys, S. (2012). Empirical evidence on the effects of tax incentives. *International Tax and Public Finance*, 19(3), 393-423.
- ITU (2018). Measuring the information society report. ict country profiles. Report 2, Geneva.
- Jeanjean, F. (2015). What causes the megabyte price drop in the mobile industry? *Economia e Politica Industriale*, 42(3):277–296.
- Karacuka, M., Haucap, J., and Heimeshoff, U. (2011). Competition in Turkish mobile telecommunications markets: Price elasticities and network substitution. *Telecommunications Policy*, 35(2):202–210.
- Kathuria, R., Uppal, R., and Mamta (2009). An econometric analysis of the impact of mobile. Policy Paper 9, UK.
- Koutroumpis, P., Lekatsas, A., Giaglis, G., and Kourouthanasis, P. (2011). Between a rock and a hard place: Recession and telecoms taxation. *Telecommunications Policy*, 35(7):681–688.
- Lambrecht, A. and Skiera, B. (2006). Paying too much and being happy about it: Existence, causes, and consequences of tariff-choice biases. *Journal of marketing Research*, 43(2):212–223.
- Lee, D. H. and Lee, D. H. (2006). Estimating consumer surplus in the mobile telecommunications market: The case of Korea. *Telecommunications Policy*, 30(10):605–621.
- Li, W., Qiang, C. Z.-W., and Xu, L. C. (2005). Regulatory reforms in the telecommunications sector in developing countries: The role of democracy and private interests. *World Development*, 33(8):1307–1324.
- Madden, G., Coble-Neal, G., and Dalzell, B. (2004). A dynamic model of mobile telephony subscription incorporating a network effect. *Telecommunications Policy*, 28(2):133–144.
- Martins, M. L. C. (2003). International differences in telecommunications demand. *Information Economics and Policy*, 15(3):291–303.
- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, 49(6):1417–1426.

- OECD (2012). Stryszowska, M., Estimation of Loss in Consumer Surplus Resulting from Excessive Pricing of Telecommunications Services in Mexico (*OECD Digital Economy Papers* No. 191, 2012).
- Phlips, L. (1971). Substitution, complementarity, and the residual variation around dynamic demand equations. *The American Economic Review*, 61(4):586–597.
- Qiang, C. Z.-W. and Pitt, A. (2003). *Contribution of information and communication technologies to growth*. The World Bank.
- Rogers, E. M. (1976). New product adoption and diffusion. *Journal of consumer Research*, 2(4), 290-301.
- Roller, L.-H. and Waverman, L. (2001). Telecommunications Infrastructure and Economic Development: A Simultaneous Approach. *American Economic Review*, 91(4):909–923.
- Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, 71(1):135–158.
- Rota-Graziosi, G., & Sawadogo, F. (2020). The tax burden on mobile network operators in Africa.
- Sexauer, B. (1977). The role of habits and stocks in consumer expenditure. *The Quarterly Journal of Economics*, 91(1):127–142.
- Swamy, S. (1968). A dynamic, personal savings function and its long-run implications. *The Review of Economics and Statistics*, 50(1):111–116.
- Taylor, L. D. and Houthakker, H. S. (2009). *Consumer demand in the United States: Prices, income, and consumption behavior*. Springer Science & Business Media.
- Tsionas, M. (2019). *Panel Data Econometrics: Empirical Applications*. Academic Press.
- Vogelsang, I. (2017). Regulatory inertia versus ICT dynamics: The case of product innovations. *Telecommunications Policy,* 41(10), 978-990.
- Waverman, L., Meschi, M., and Fuss, M. (2005). The impact of telecoms on economic growth in developing countries. *The Vodafone policy paper series*, 2(03):10–24.
- Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step gmm estimators. *Journal of Econometrics*, 126(1):25–51.

Appendices

Table A.1: Descriptive statistics for the global sample

	Observations	Mean	Standard deviation	Minimum	Maximum
Minutes of use per subscriber	4,486	990.8	609.6	88.46	4,340
Effective price per minute	4,486	0.0890	0.106	0.000122	1.035
Effective price per megabyte	980	0.0391	0.160	7.61e-05	2.206
GDP per capita	4,468	21,133	19,414	510.8	90,918
SIMpsubs	4,486	1.677	0.285	1.050	2.779
fixed	1,159	48.76	28.39	0.900	100
mobile	1,286	84.68	13.83	19.94	102.4
computers	4,380	52.58	26.94	2.630	95.40
regulation	3,948	74.23	18.73	7.500	97.33
contmp	4,485	0.136	0.123	0	0.676
prepmp	4,465	0.240	0.153	0	1.019

Table A.2: Descriptive statistics for the developing countries sample

	Observations	Mean	Standard deviation	Minimum	Maximum
Minutes of use per subscriber	2,261	1,050	666.5	88.46	3,495
Effective price per minute	2,261	0.0398	0.0460	0.000122	0.400
Effective price per megabyte	735	0.0423	0.182	7.61e-05	2.206
GDP per capita	2,243	5,535	3,657	510.8	14,933
SIMpsubs	2,261	1.775	0.300	1.075	2.779
fixed	771	32.96	18.84	0.900	96.05
mobile	777	82.13	15.78	19.94	102.4
computers	2,179	31.68	20.65	2.630	76.16
regulation	2,126	67.89	20.05	7.500	95
contmp	2,260	0.0573	0.0647	0	0.390
prepmp	2,240	0.286	0.162	0.00130	1.019

Table A.3: Descriptive statistics for the developed countries sample

	Observations	Mean	Standard deviation	Minimum	Maximum
Minutes of use per subscriber	2,225	930.4	539.2	244.3	4,340
Effective price per minute	2,225	0.139	0.125	0.0112	1.035
Effective price per megabyte	245	0.0294	0.0527	0.000800	0.537
GDP per capita	2,225	36,858	15,837	10,538	90,918
SIMpsubs	2,225	1.577	0.231	1.050	2.394
fixed	388	80.14	14.89	37.77	100
mobile	509	88.57	8.842	57.60	100
computers	2,201	73.28	12.69	29.40	95.40
regulation	1,822	81.62	13.76	20.17	97.33
contmp	2,225	0.215	0.117	0.00200	0.676
prepmp	2,225	0.193	0.129	0	0.755

Table A.4: Variable definition and source

Variables	Definition	Source
lmns	Log of the total number of minutes of use per unique subscriber. Total minutes of use is defined as the "total minutes, including incoming, outgoing and roaming calls, transferred over the mobile network in the period." Total subscribers are defined as "Total unique users who have subscribed to mobile services at the end of the period, excluding M2M. Subscribers differ from connections such that a unique subscriber can have multiple connections."	GSMAi
lp	Log of the effective price per minute. The effective price per minute is defined as the ratio of the total voice revenue (turnover) to the total number of minutes of use. Voice revenue is defined as the "recurring (service) revenue generated from voice services in the period". Total minutes of use is defined as the "total minutes, including incoming, outgoing and roaming calls, transferred over the mobile network in the period.".	GSMAi
lpd	Log of the effective price per megabyte (MB). The effective price per MB is defined as the ratio of the total data revenue (turnover) to the total data traffic in MB. Data revenue is defined as the "recurring (service) revenue generated from data (non-messaging) services in the period". Total data traffic is defined as the "total data traffic transferred over the mobile network in the period, expressed in gigabytes (GB)." However, we convert it to megabytes (MB).	GSMAi
lgdp	Log of the GDP per capita in constant 2010 USD.	WDI
SIMpsubs	Number of SIMs per unique subscriber is the total unique active SIM cards per subscriber at the end of the period.	GSMAi
fixed	It represents the "proportion of households with a fixed line telephone."	ITU
mobile	It represents the "proportion of households with a mobile cellular telephone."	ITU
computers	Estimated proportion of households with a computer	ITU
regulation	ITU ICT overall regulatory score. "It pinpoints the changes taking place in the ICT regulatory environment. It facilitates benchmarking and the identification of trends in ICT legal and regulatory frameworks. The Tracker does not measure the quality, the level of implementation or the performance of regulatory frameworks in place, but records their existence and features."	ITU ICT regulatory tracker
contmp	"Contract (postpaid) connections at the end of the period, expressed as a percentage share of the total market population. A contract tariff is such that usage is billed at the end of each service period and a contract is signed for the service, typically for a fixed-term."	GSMAi
prepmp	"Prepaid connections at the end of the period, expressed as a percentage share of the total market population. A prepaid tariff is such that credit is purchased in advance of service use."	GSMAi

Table A.5: Summary of selected empirical studies

Author(s)	Sample	Period of study	Estimation model	Price elasticity estimates
Das and Srinivasan (1999)	India & 19 Indian States	1964 - 1997	Time series and panel models	-0.58
Röller and Waverman (2001)	21 OECD countries	1970 - 1990	Simultaneous equations model with GMM	-1.13
Martins (2003)	74 developing and developed countries	1980 and 1985	Deaton–Muellbauer Iterative (DMI) procedure	. Static model (Rich countries: -1.43; Poor countries: -1.62) . Dynamic model (Rich countries: -2.29; Poor countries: -2.42)
Madden et al. (2004)	56 countries	1995 - 2000	Panel fixed effects	. Global sample: - 0.55 . High income countries: -0.53
Waverman et al. (2005)	92 low and high income countries	1980 - 2003	system of 3 equations using GMM	-1.5
Lee and Lee (2006)	Korea	M1 1996 - M12 2004	OLS and GLS	. Pre-competition period: -0.9 . Post-competition period: -0.609
Garbacz and Thompson (2007)	53 developing countries	1996 - 2003	Panel fixed effects and IV method	. Connection charge: -0.37 to -0,029 . Monthly charge: -1.268 to -0.195
Dewenter and Haucap (2008)	3 Austrian mobile operators	M1 1998 - M3 2002	Difference-GMM	. Business tariffs (Short-Run (SR): -0,33 and Long-Run (LR): -0,74) . Private consumer tariffs (SR: -0,14 and LR: -0,37) . Postpaid tariffs (SR: -0,24 and LR: -0,67) . Prepaid tariffs (SR: -0,08 and LR: -0,20) . Among the 3 mobile operators (SR: -0,26 to -0,40 and LR: -0,47 to -1,10)
Kathuria et al. (2009)	19 Indian States	1999 - 2008	Panel 3SLS	. Global: - 2.12 . states with high penetration : -1.87 . states with low penetration: -1.92
Koutroumpis et al. (2011)	3 Greek mobile operators	2005 - 2010	Generalized least square (GLS)	-1.645
Caves (2011)	38 US States	2001 - 2007	Panel 2SLS and 3SLS	. Wireless: -1.76 to -1.63 . Wireline: -0,57 to -0.54
Karacuka et al. (2011)	5 Turkish mobile operators	M1 2006 - M12 2006	Difference-GMM	. Entire market (SR: -0,28 and LR: -0,45) . Prepaid market (SR: -0,36 and LR: -0,33) . Postpaid market (SR: -0,20 and LR: -0,72)
Hausman and Ros (2013)	17 countries, including 9 OECD countries, 5 Latin American countries, and 5 Asian countries	Q2 2004 - Q3 2011	Panel fixed effects and difference-GMM	. SR: -0.10 and . LR: -0.476
Hakim and Neaime (2014)	Middle East and North African countries	1995 - 2007	Panel 2SLS	-1.241 to -1.008