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The Effects of Mobile Phone Infrastructure: Evidence from Rural Peru

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ABSTRACT

We exploit the timing of cell phone coverage in rural Peru to investigate its effects on economic development. We exploit information regarding the location, date of installation and technical characteristics of cell phone towers in order to construct coverage patterns at the village level from 2001 through 2007. We then merge this information with national household surveys spanning the same period. Estimates suggest an increase of 7 percentage points in the likelihood of self reported cell phone ownership after coverage, an increase of 7.5 percent in yearly household expenditures, and a 13.5 percent increase in the value of assets.

Keywords: Mobile coverage; economic development.

JEL classification: O1; O3; Q13; Q16

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1 Introduction

Over the past twenty years, there has been an explosion in the use of mobile telephones worldwide. Initially, this increase was concentrated in industrialized nations, but the remarkable recent trend has been the quick adoption of mobile telephones in the developing world. While mobile phone use was slower to take-off in developing countries (see Figure 1), with only one subscription per hundred inhabitants in 1997, this increased to over one in ten by 2000, and reached almost one in two by 2007. This quick adoption of mobile phones has been viewed with excitement by those in the development community, as there is widespread belief that mobile phones will lead to income growth in poor countries. A recent World Bank report argues that "the development potential of the wireless platform is enormous" (Khalil et al., 2009), and *The Economist* asserts that "poor countries have already benefited hugely from mobile phones." (Economist, 2009)

One reason for the excitement about mobile phones as a tool for development is that low income countries have lagged behind in infrastructure, including land based telecommunications. For example, in 1997, there were nearly ten times more fixed lines per capita in developed countries than there were in developing countries (see Figure 1). This infrastructure gap has long been identified as a possible explanation for why poor countries remain poor. One advantage of mobile telephone infrastructure is that it can be deployed without the expensive network of wires necessary for land based phones. As a result, mobile phones can allow developing countries to *leapfrog* a technology on which they have long lagged, and quickly adopt a better technology. As a result, if the infrastructure gap has indeed been part of the problem for income growth in developing countries, then mobile telephones may be helping these countries to close the gap. This is even more true in rural areas of developing countries, since these areas had the least access to telecommunications technology prior to the introduction of mobile phones, and are experiencing explosive adoption rates for this new technology.

Despite the pervasive belief that mobile phones are beneficial for developing countries, the research on this topic lags behind. The exceptions are Jensen (2007), which examines how mobile phones impact the market for fresh fish in Kerala, India, and Aker (2008), which studies the impact of mobile phones on the market for grain in Niger. These papers provide insight into how mobile phones transform the way that a market operates. At the same time, since both restrict their analysis to the impact of mobile phones on a particular commodity, there remains no systematic evidence of the overall impact of mobile phones on a representative sample of producers and consumers across multiple sectors. To help fill this gap, we set out to provide such evidence, estimating the impact of mobile phone infrastructure on household well-being in rural Peru between 2001 and 2007.

If cell phones improve the well-being of market participants, there is also the question of how these gains are distributed. Jensen (2007) finds the cellphones improve both producer and consumer welfare, while Aker (2008) finds that mobile phones improve trader and consumer welfare, but does not analyze the impact on producer welfare. In the developing country context, where most households are engaged in some form of home farming, it is extremely important to understand how mobile phones impact the profits of home producers in order to assess the overall impact on household well-being. Also, if the distribution of gains differs by commodity, then it is vital conduct this analysis across commodities. This paper does just that, analyzing the impact of mobile phone coverage on the production and consumption patterns of a representative sample of rural households in Peru.

Another question that has arisen in this literature is whether spill-over benefits accrue to those who do not own phones, but live in areas that have gained mobile phone coverage. Jensen (2007) finds that producers without mobile phones do gain, although not as much as those who own mobile phones. On the consumption side, this paper does not look at heterogeneous effects for owners vs. non owners, which are possible if mobile phone owners are able to find lower prices when making purchases. To shed additional light on this topic, we examine whether there is evidence of spillover effects for those who do not own a phone, both for the production and consumption side.

In future work, we plan to extend this intuition – that mobile phones may improve household well-being, but that it is also important to understand how these gains are distributed. For example, we will examine whether the benefits are larger in areas that had no access to landlines prior to the introduction of mobile phones. We will also examine whether cell phones benefited the poorest of the poor, or if the gains were concentrated amongst those who were relatively advantaged within these communities.

The paper proceeds as follows. In Section 2, we review the existing literature and discuss the theoretical rationale for why mobile phones may impact household well-being. In Section 3, we provide information on the context of Peru, discussing the mobile phone market and introducing our data sources. In Section 4, we lay out our empirical strategy, and we provide our empirical results in Section 5. In Section 6, we summarize our conclusions.

2 Theory & Literature Review

Before laying out an empirical strategy for measuring the impact of mobile phone coverage on household well-being, we must first provide a rationale for why mobile phones may be welfare enhancing. Jensen (2007), in arguing that mobile phones will have an impact on markets in Kerala, India, points to one of the basic tenets of economics, the First Fundamental Theorem of Welfare Economics. This theorem demonstrates that a competitive equilibrium resulting from utility and profit maximizing agents will always be Pareto efficient. In other words, the invisible hand of the market will always produce an allocation of resources such that it is not possible to make any agent better off without making another agent worse off. It has long been recognized, however, that this result relies on critical assumptions, among which are the existence and efficient operation of markets for all commodities. If these assumptions are not satisfied, then welfare maximizing agents may produce an allocation of resources that is not Pareto efficient. In fact, the Greenwald-Stiglitz Theorem (Greenwald and Stiglitz, 1986), demonstrates that incomplete information can result in deviations from Pareto efficiency. If the introduction of mobile phones enhance the spread of information, then there is the potential to improve the functioning of markets, which would make it possible to make some agents better off without making any agents worse off.

This idea, that improved information technology can enhance the functioning of markets, has gained substantial empirical support. This literature has relied on the fact that, if markets are operating efficiently, then the price difference for an identical good being sold at two markets should be no greater than the cost of transporting the commodity from one market to the other. Moreover, if the introduction of better communications technology reduces the price differences across markets, then this provides convincing evidence that communication technology has improved market efficiency. Garbade and Silber (1978) argue that the introduction of the telegraph and the trans-Atlantic cable reduced price differentials across markets. Jensen (2007) shows that the introduction of mobile phone coverage causes a remarkable reduction in the variability in fresh fish prices, both across markets and over time, and Aker (2008) obtains similar results for grain prices in Niger. Finally, Goyal (2010) provides evidence suggesting that soy price dispersion across markets in Madhya Pradesh, India, decreases following the introduction of Internet kiosks.

While there is a clear theoretical argument for why improvements in communications technology should enhance market efficiency, it is less clear how the economic gains will be distributed across market participants. As stated in Jensen (2007), "How the net welfare gain is shared between the two groups, and whether, in fact, one group gains while the other loses in response to increased arbitrage, is *a priori* ambiguous." Search-theoretic models can sometimes be used to generate useful predictions, such as when only one side of the market is engaged in search and mobile phones reduce the cost of that search. Predictions, however, become more difficult when both sides of the market are searching, and when mobile phones reduce the cost of search for all agents simultaneously. Consequently, it is difficult to generate predictions regarding the impact of mobile phone infrastructure, since mobile phone coverage is rolled out to entire markets at once, providing simultaneous benefits to farmers, middlemen, and consumers. Given this, the impact of mobile phones on the well-being of producers, consumers, and middlemen remains an empirical question. Jensen (2007) provides evidence that, at least for the fresh fish market in Kerala, India, both fishermen and fish consumers are better off following the introduction of mobile phones. This is because average fish prices decline, generating an increase in consumer surplus. While this same price decrease lowers fishermen profits, this effect is more than offset by an increase in the quantity sold and a simultaneous reduction in the fraction of wasted production (i.e., catch that was going unsold and being dumped back to sea). Looking at grain markets in Niger, Aker (2008) provides evidence that both traders and consumers gain. In that context, traders receive increased profits due to an increase in the sales price, and consumers are better off because the consumer price of grain decreases. The fact that consumer and trader prices move in opposite directions, however, suggest reduced profits for middlemen, and the paper does not measure the welfare impact for farmers.

3 Data & Context

In 1998, the cell phone market of Peru was dominated by two mobile phone networks, Nextel del Peru and Telefónica del Peru, and service was available only in Lima and a few other densely populated urban centers. By 2001, these providers had expanded their coverage to most of the urban areas of Peru, particularly along the Pan-American Highway, which runs down the coast, and along which more than half of the Peruvian population resides. While coverage was quite pervasive along the coast and in other urban centers by 2001, there was little coverage in less densely populated areas, such as the Peruvian jungle and highlands. In 2000, however, a new license was sold to TIM Peru, which was later sold and rebranded as Claro Peru. In 2001, this new provider and Telefónica began aggressively expanding their networks into less densely populated areas. The extent of this expansion can be seen in Figure (2) and Figure (3), which show the locations of all the mobile phone towers in 2001 and 2007, respectively. This paper exploits this dramatic change in the availability of mobile phone coverage in rural areas between 2001 and 2007 to measure the impact of mobile phone coverage on household outcomes in Peru. In order to conduct this evaluation, we rely on several data sources, which we now describe in detail.

For our household data, we use the Peruvian National Household Survey (Encuesta Nacional de Hogares, ENAHO), an annual household survey collected by the Peruvian National Institute of Statistics and Informatics (Instituto Nacional de Estadística e Informática, INEI). This is a comprehensive household survey, providing us with information on household demographics, labor force behavior, home production, and expenditures. This data provides us with a nationally representative repeated cross-section of Peruvian households. From this data, we select only those observations that are living in rural communities. We focus on rural areas because, by 2001, the first year that ENAHO was conducted, mobile phone coverage was already widely available in urban areas, so we do not have the variation in mobile coverage necessary to identify the impact of mobile phones on urban households.

We also use data from the Fund for Investment in Telecommunications (Fondo de Inversión en Telecomunicaciones, FITEL), an independent agency that reports to the Peruvian Ministry of Transportation and Communication (Ministerio de Transportes y Comunicaciones). This data contains the construction date of every mobile phone tower in Peru, as well as detailed tower characteristics, such as its location, height, transmission power and transmission frequency. We use these tower characteristics to simulate mobile coverage areas in each year. This simulation was performed using Radio Mobile, a freely available software package developed by Roger Coudé. This software implements the Longley-Rice model, also known as the Irregular Terrain Model (ITM), to simulate signal propagation. The algorithm takes into account geographic terrain (using 90m resolution elevation data from the Shuttle Radar Topography Mission), the curvature of the earth, and tower characteristics, such as transmission strength, antenna type, height, gain and reception limits.

Using these simulated coverage maps, we determine the year in which each ENAHO village gained mobile phone coverage. Note that we are unable to determine the physical location of some ENAHO villages, so these data are dropped from our analysis. This amounts to 15% of the rural ENAHO households. The extent of missing geographic information varies across years, reaching as high as 56% in 2004 – although our results are robust to dropping 2004 from the analysis. Aside from 2004, the year with the greatest number of lost observations is 2006, where we are unable to determine the location of 10% of rural households.

4 Methodology

We employ several empirical strategies in order to identify the impact of mobile phone infrastructure on household outcomes. As our baseline specification, we simply regress the outcome variable on mobile phone coverage:

$$y_{ivt} = \beta_0 + \beta_1 \text{coverage}_{vt} + \mu_t + \epsilon_{ivt}$$

where i indexes the household, v indexes the village, t indexes the year, y is the outcome of interest, μ_t is a year fixed effect, and coverage is a dummy variable indicating whether the village is within a mobile phone coverage area. Standard errors are clustered at the village level, in order to allow for correlated errors across households in the same village.

If coverage is uncorrelated with the error term (ϵ), this strategy will produce unbiased estimates of the impact of mobile phone coverage. However, since it is in the best interest of mobile phone providers to place their towers in locations that are profit maximizing, it is unlikely that coverage is uncorrelated with ϵ. More likely, towers are positioned to maximize the number of subscribers per dollar spent on infrastructure, in which case coverage would be more likely in areas with greater population density and higher per capita income. Since these variables may have a direct impact on the outcome variables of interest, the results from this strategy are potentially biased.

We can provide some empirical support for the fact that mobile phone coverage is, indeed, targeted to wealthier villages. Table (1) compares the characteristics of households that are never treated to those that are treated. To side-step the possibility that households with coverage have higher income and expenditures precisely because mobile phones foster economic development, we focus on the comparison between the first column, which contains means for households in areas that are never covered, with the second column, which contains means for households in areas that will be covered in the future, but were not yet covered. Households that will be covered in the future have consistently higher expenditures and income than households that will never be covered. This provides strong evidence that mobile phone providers are not picking their coverage areas randomly, but are instead targeting service toward particular villages and households.

Given the non-random placement of mobile phone coverage, we also employ a second specification with village fixed effects:

$$y_{ivt} = \beta_0 + \beta_1 \text{coverage}_{vt} + \mu_v + \mu_t + \epsilon_{ivt}$$

where μ_v is a village fixed effect. This fixed effect controls for any time invariant village characteristics that may influence the mobile phone provider's decision of where to locate their towers.

While this specification eliminates tower placement bias if cell phone providers base their decisions on fixed village characteristics, such as population or per capita income, there is still the potential for bias due to tower placement if mobile phone providers target coverage based on time-varying village characteristics. For example, if mobile phone providers consider the future and maximize the net present value of future subscription revenue, then they may attempt to target villages that are expected to experience higher than average population or economic growth over the coming years. If this is the case, then what appears to be an impact of mobile phones on household outcomes could simply be an artifact of the fact that covered villages have higher than average income or population growth.

In order to assess this concern, we employ a model that allows the impact of coverage to vary with the number of years of coverage:

$$y_{ivt} = \beta_0 + \sum_{y \neq 0} \beta_y [\text{years covered} = y]_{vt} + \mu_v + \mu_t + \epsilon_{ivt}$$

where [years covered $= y$] is a dummy variable indicating whether the village has been covered exactly y years. By including negative years of coverage in this specification, we can assess whether there are trends in the outcome variables leading up to the first year of coverage. If there are no such trends, then it seems unlikely that mobile phone providers are basing their coverage decisions on time-varying village characteristics, in which case specifications with village fixed effects should provide unbiased estimates of the effects of mobile phone coverage on household outcomes.

5 Results

5.1 Baseline Specification

We begin our analysis of the impact of mobile phones on household well-being with our baseline empirical specification, which simply regresses household outcomes on village coverage status. These results, shown in Table 2, suggest that coverage has a strong positive impact on cell phone ownership, household wage income, assets, and expenditures. The magnitude of these effects are large, with wage income increasing by 57% and total expenditures increasing by 61%.

In the methodology section, however, we provide evidence that high income and expenditure villages were more likely to receive coverage. As a result, the correlation between coverage and income in this specification could be a result of reverse causality, with better economic outcomes causing coverage, rather than being evidence that coverage causes better economic outcomes.

5.2 Village Fixed Effects

In order to mitigate concern regarding non-random tower placement, Table 3 implements village fixed effects. This specification is robust to non-random placement of towers, so long as tower placement depends only on time-invariant village characteristics. Relative to the baseline statistical specification, the impacts of coverage are much more muted. Nonetheless, the results suggest that coverage has a substantial impact on mobile phone ownership, which increases by 7%. Coverage does not have a statistically significant impact on wage income or on asset ownership, but is associated with an 8% increase in log total expenditures.

5.3 Duration of Treatment

While village fixed effects address the concern that tower placement may depend on time-invariant factors, the results may still be biased if tower placement depends on time-varying village characteristics. For example, if mobile phone coverage providers place their towers in areas that are expected to experience faster than average economic growth, than it may erroneously appear that mobile phones are causing economic growth. In order to investigate this concern, we implement a model that allows for heterogeneous impacts by duration of treatment. The results from this specification are shown in Table (4). Note that all the coefficients in this table show effect sizes relative to the omitted group of zero years of coverage.

The first conclusion to draw from the treatment duration results is that, for all eight outcomes, there are no statistically significant differences prior to treatment. Since there are no statistically significant pre-coverage trends, we find no evidence that mobile phone providers targeted coverage toward areas that were experiencing faster than average income or expenditure growth. Given this, we conclude that the post-treatment effects are not an artifact of tower placement, unless mobile phone providers were somehow able to anticipate future economic growth above and beyond trends that were observable at the time the towers were built.

In addition to providing evidence on the extent of bias due to non-random tower placement, this specification also sheds light on how effect sizes vary with the number of years of coverage. Turning to our results, we find that mobile phone ownership jumps immediately, with an increase of 4.6% in the year after coverage, and rising to 29% six years after coverage. There is also a statistically significant increase in wage income of 15% two years after coverage, and this increase to 34% after six years of coverage. While there is no impact on the proportion of households that own any assets, the value of household assets increases by 23% two years after coverage, and increases to 54% after six years of coverage. Finally, total household expenditures increase by 10% after one year of coverage, and increase to 45% after six years of coverage. Initially this increase in expenditures appears to be driven by non-durable expenditures, although increases are statistically significant for all components of expenditures after five years of coverage.

5.4 Home Farm and Business Income

Thus far, we have focused on wage income, but most households in developing countries also operate home farms – so in order to pin down the impact of mobile phone coverage on household well-being, it is important to consider the impact on farming profits. These results are shown in Table (5). We find a statistically significant increase in the fraction of households running a home farm for one of the five post-treatment coefficients. In addition, the prevalence of home farming is lower two and three years prior to treatment, suggesting that this effect may simply be picking up a pre-treatment trend in covered areas. There are several possible explanations for such a trend. First, it could be that mobile phone providers targeted areas were farming was becoming more prevalent. Second, it may be that households expected mobile phone coverage would be introduced and, in anticipation of this fact, opened farms. Finally, since this is the only variable for which we find evidence of a pre-treatment trend, it may be that this is just a differential trend between covered and uncovered villages that arose by chance. We plan to explore this finding further to see if we can differentiate between these possibilities. In any event, we find that farm expenditures are higher post treatment, and this effect is statistically significant four and six years after treatment. The impact of mobile coverage on the value of farm production is not statistically significant, but the general pattern is a small decline initially, and then small increase. As a result, profits appear somewhat lower after the introduction of mobile coverage, but the effect is only statistically significant in the year immediately after the introduction of mobile phones.

We also look at the impact on home business earnings. These results can be found in Table (6). As with home farming, we find an increase in home businesses following mobile phones, and this effect is statically significant one year and five years after the introduction of coverage. Profits are higher, but the effect is small and statistically insignificant.

5.5 Robustness check: migration

One possible interpretation of the findings presented thus far is that the construction of a mobile phone tower attracts high income individuals to the area. If this is the case, then it may be that mobile phones have no actual impact on household well-being, but simply cream-skim high quality migrants. In order to rule out this possibility, we now look at the impact of mobile phone coverage on the fraction of individuals born in the district. These results are presented in Table (7). Note that there are no statistically significant impacts, regardless of treatment duration. While we have no direct measure of movement within district, it seems unlikely that migrants would be attracted from within the district but not from outside the district. Given this, we do not believe that our results are an artifact of selective migration.

5.6 Heterogeneous effects: mobile phone ownership

One final question regarding the impact of mobile phones on household well-being is how these gains are distributed within covered villages. One dimension of heterogeneity that has received attention in the literature is whether benefits go exclusively to mobile phone owners, or whether there are spillover benefits for non-owners. We explore this question in Table (8), where we show the post-coverage effects for non-owners, and the additional effects for those who do own cell phones. From this table, it is apparent that income and asset ownership are relatively flat for non-owners. While we do see a statistically significant increase in total and food expenditures for non-owners, these increases are relatively modest and, for the most part, statistically insignificant until five years after the introduction of mobile phones. The differences between owners and non-owners, however, are large and statistically significant throughout. These results are suggestive that there is little in the way of spillover benefits for those who do not own cell phones. Of course, mobile phone ownership is itself a choice, and we cannot rule out the possibility that there are spillover effects, but that those who benefit use their increased earnings to purchase a mobile phone.

6 Conclusion

There is much excitement in the development community about the potential of mobile phones for fostering increased economic growth and, thus, enhancing the well-being of households in less developed countries. At the same time, while there is convincing evidence that mobile phones enable markets to operate more efficiently, there is little empirical work establishing how this increased efficiency impacts the well-being of a typical household. In this paper, we provide evidence on this point, exploiting the roll-out of mobile phone infrastructure in rural Peru between 2001 and 2007 to measure the impact of cellular coverage on household resources. We find evidence that mobile phone coverage increases the income, assets, and expenditures of rural consumers. Moreover, we find no statistically significant impact on the profits of home businesses, which is important for understanding the overall impact on well-being in an environment such as Peru, where 85% of households operate a home farm.

In future research, we will extend this work in several directions. First, we plan to examine price data to pin down the impact of mobile phones on price variation across villages, and to measure the impact of mobile phones on the average price paid (on the consumption side) or received (on the production side). We also hope to measure the impact of mobile phone coverage on the diffusion of new technologies. Finally, we will explore the possibility that mobile phones reduce the costs of communication with friends and family outside the village, and thus strengthen the use of extended families as a form of insurance against unanticipated shocks.

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Figure 1: Mobile phone subscriptions and fixed lines per 100 inhabitants, 1997-2007

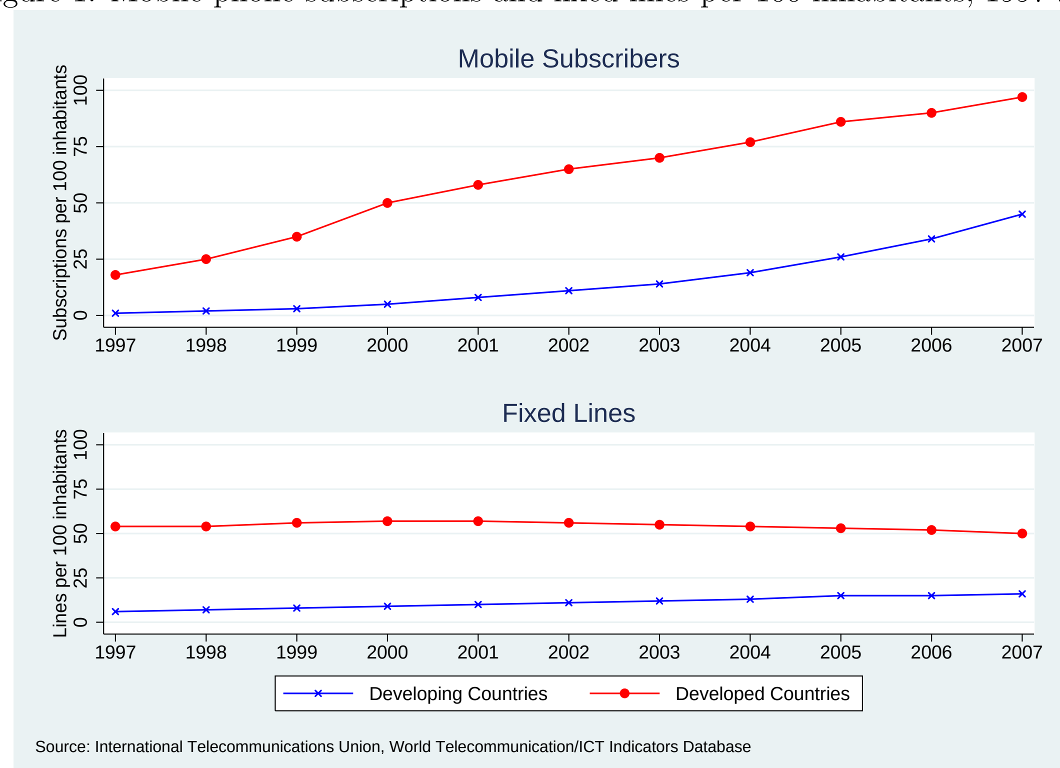


Figure 2: Map of Mobile Towers, 2001

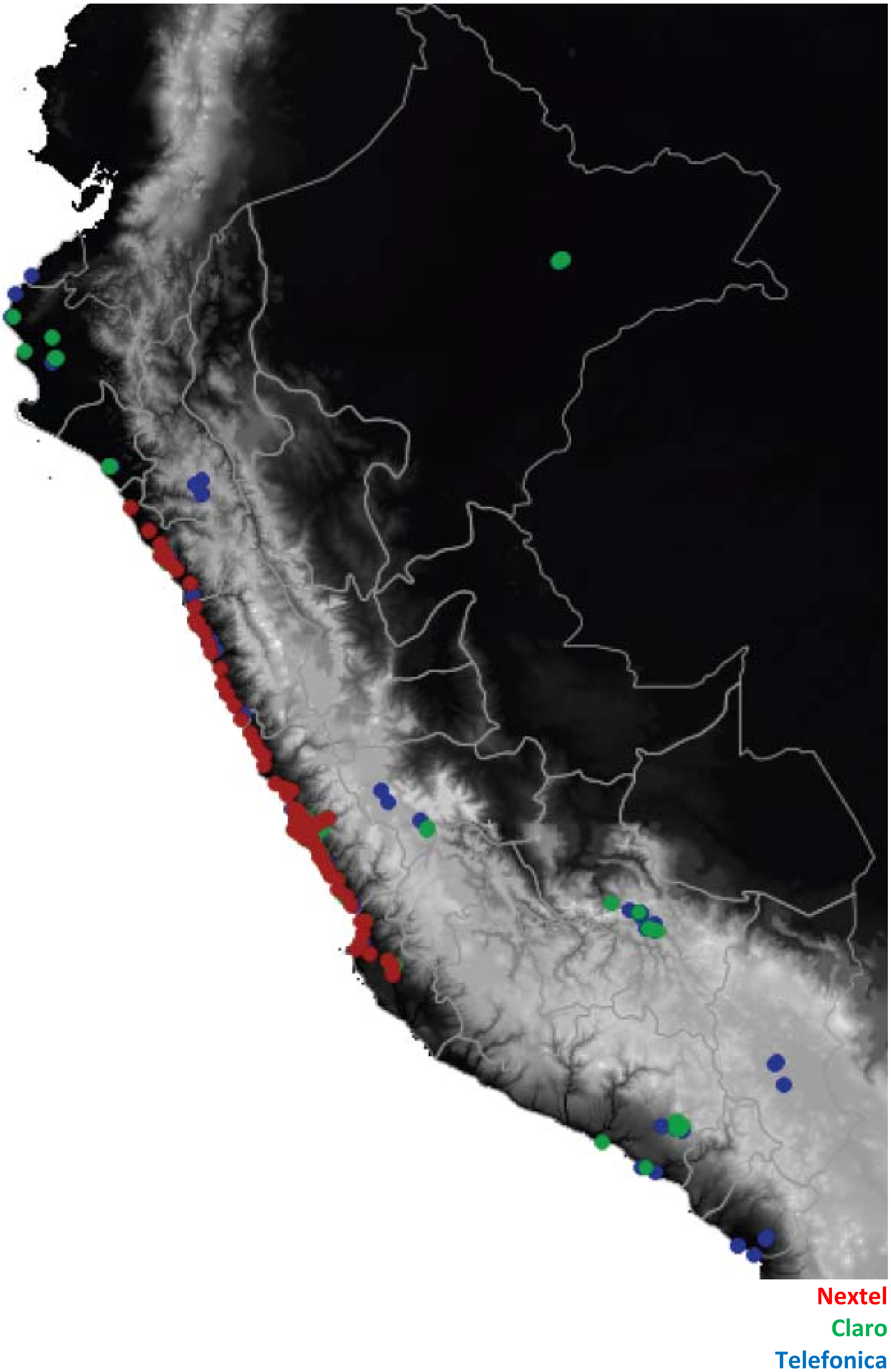
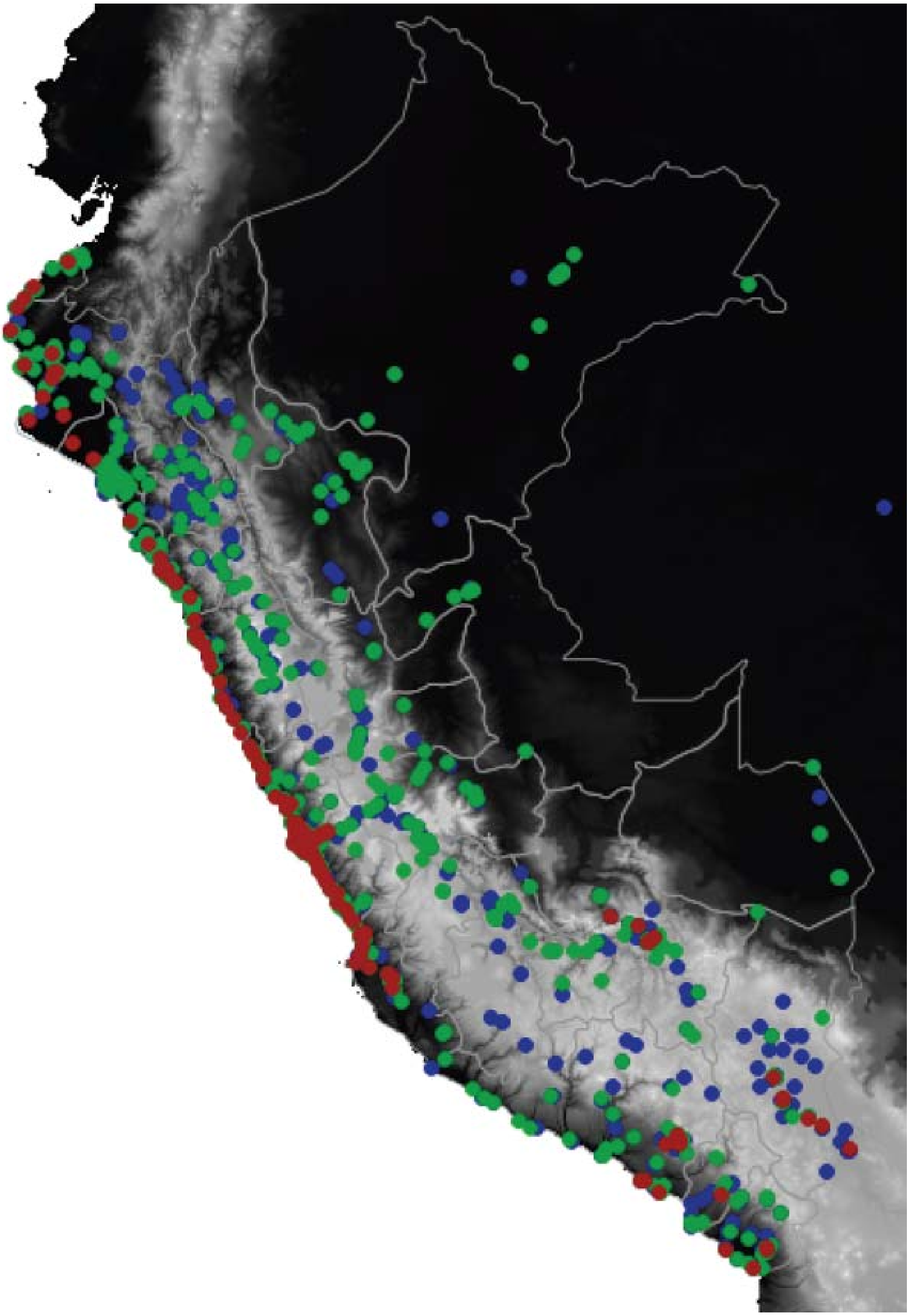


Figure 3: Map of Mobile Towers, 2007



Nextel
Claro
Telefonica

Figure 4: Mobile coverage, ownership, and fixed line prevalence in rural Peru, 2001-2007

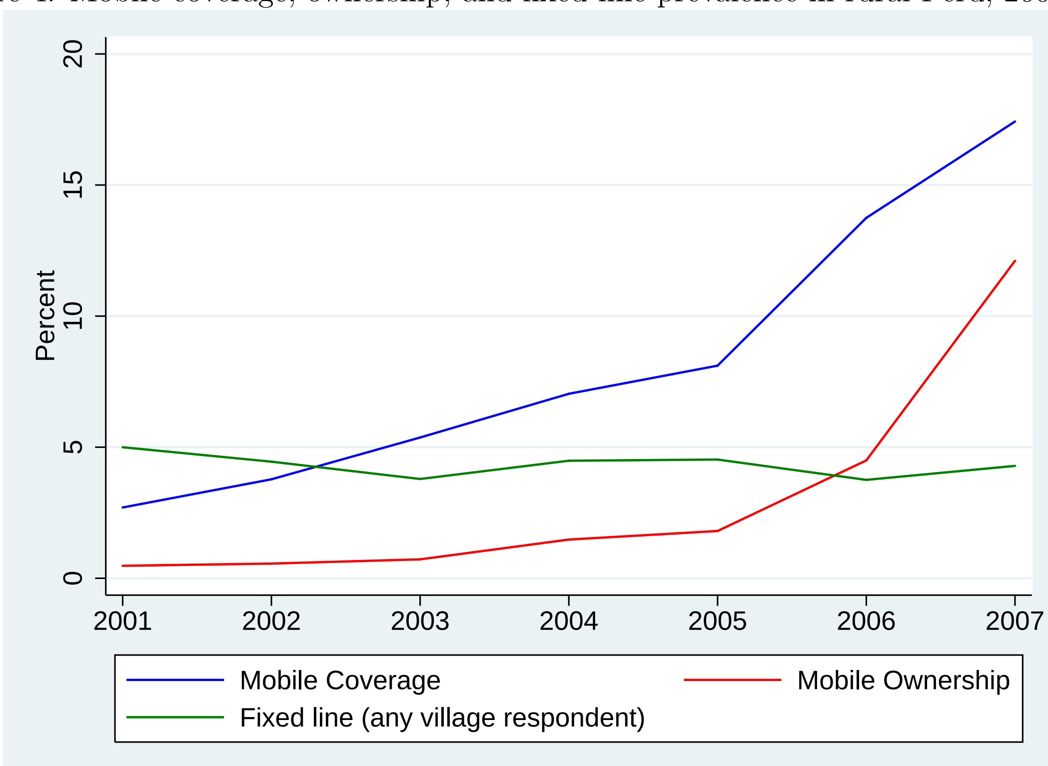


Table 1: Comparing Covered and Uncovered Households

	Coverage Status		
	Never Covered	Pre-Coverage	Post-Coverage
2001 Expenditures	214.7	302.3	402.5
	(2.9)	(9.2)	(30.8)
2002 Expenditures	214.2	277.4	353.9
	(2.4)	(7.8)	(15.6)
2003 Expenditures	224.2	333.2	362.7
	(3.1)	(10.8)	(16.4)
2004 Expenditures	245.2	361.7	423.7
	(3.9)	(18.7)	(22.8)
2005 Expenditures	224.8	329.1	451.5
	(2.8)	(12.7)	(15.9)
2006 Expenditures	239.9	351.4	433.2
	(2.8)	(14.3)	(13.8)
2007 Expenditures	253.2	.	445.2
	(3.0)	(.)	(11.8)
2001 Income	437.6	634.5	763.3
	(7.7)	(44.7)	(107.8)
2002 Income	428.9	578.0	742.4
	(6.5)	(23.2)	(43.6)
2003 Income	418.2	669.0	746.2
	(6.9)	(80.0)	(39.3)
2004 Income	465.7	615.8	801.5
	(11.7)	(35.7)	(57.9)
2005 Income	440.2	550.9	834.8
	(8.2)	(24.6)	(38.2)
2006 Income	495.6	634.6	946.5
	(8.8)	(34.7)	(105.1)
2007 Income	531.8	.	895.8
	(10.2)	(.)	(31.2)

Standard errors in parentheses

Table 2: Regression models

					Log Expenditures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Has Mobile	Log Income	Has Assets	Log Assets	Total	Food	Non-Food	Durable
coverage	0.151***	0.565***	0.119***	0.711***	0.606***	0.712***	0.503***	0.158***
	(0.010)	(0.030)	(0.009)	(0.048)	(0.026)	(0.027)	(0.031)	(0.041)
N	42335	40093	42335	28508	42148	41248	41850	32689

Standard errors in parentheses, clustered at the village (CCPP) level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 3: Regression models with village fixed effects

					Log Expenditures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Has Mobile	Log Income	Has Assets	Log Assets	Total	Food	Non-Food	Durable
coverage	0.072***	0.040	-0.029	0.135*	0.075*	0.061	0.089	-0.095
	(0.014)	(0.044)	(0.018)	(0.062)	(0.035)	(0.036)	(0.047)	(0.084)
N	42335	40093	42335	28508	42148	41248	41850	32689

Standard errors in parentheses, clustered at the village (CCPP) level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 4: Duration of coverage regression models with village fixed effects

					Log Expenditures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Has Mobile	Log Income	Has Assets	Log Assets	Total	Food	Non-Food	Durable
before3	-0.013	-0.059	0.005	-0.037	-0.063	-0.036	-0.045	-0.122
	(0.010)	(0.051)	(0.024)	(0.070)	(0.048)	(0.046)	(0.069)	(0.108)
before2	-0.003	0.072	0.005	0.059	-0.009	0.038	0.011	0.055
	(0.013)	(0.071)	(0.034)	(0.106)	(0.063)	(0.057)	(0.084)	(0.129)
before1	-0.006	-0.039	-0.029	-0.092	-0.009	-0.000	-0.007	0.009
	(0.012)	(0.052)	(0.027)	(0.077)	(0.046)	(0.048)	(0.065)	(0.105)
after1	0.046**	-0.013	-0.027	0.082	0.049	0.047	0.066	-0.151
	(0.015)	(0.052)	(0.024)	(0.078)	(0.045)	(0.046)	(0.060)	(0.100)
after2	0.112***	0.145*	-0.043	0.229*	0.105*	0.112*	0.126	0.024
	(0.025)	(0.068)	(0.032)	(0.112)	(0.053)	(0.053)	(0.075)	(0.130)
after3	0.104***	0.069	-0.037	0.233	0.094	0.094	0.155	0.021
	(0.028)	(0.077)	(0.028)	(0.125)	(0.059)	(0.060)	(0.084)	(0.159)
after4	0.198***	0.213*	-0.069	0.156	0.188**	0.114	0.193*	0.317*
	(0.033)	(0.087)	(0.058)	(0.164)	(0.067)	(0.071)	(0.093)	(0.153)
after5	0.182***	0.268**	-0.044	0.430**	0.384***	0.361***	0.290**	0.319*
	(0.031)	(0.092)	(0.046)	(0.150)	(0.073)	(0.074)	(0.098)	(0.158)
after6	0.291***	0.340***	-0.038	0.538**	0.446***	0.369***	0.372***	0.446*
	(0.038)	(0.094)	(0.040)	(0.168)	(0.073)	(0.073)	(0.100)	(0.174)
N	42335	40093	42335	28508	42148	41248	41850	32689

Standard errors in parentheses, clustered at the village (CCPP) level

* p<0.05, ** p<0.01, *** p<0.001

Table 5: Home farm outcomes

	(1) Has Home Farm	(2) Production	(3) Expenditures	(4) Profit
before3	-0.053*	-0.410	-0.194	-0.243
	(0.021)	(0.312)	(0.225)	(0.289)
before2	-0.064*	1.154	-0.255	1.337
	(0.030)	(1.357)	(0.389)	(1.259)
before1	-0.014	-0.783	-0.013	-0.744
	(0.019)	(0.560)	(0.272)	(0.541)
after1	0.020	-0.664	0.196	-0.846*
	(0.021)	(0.455)	(0.336)	(0.414)
after2	0.021	-0.915	0.859	-1.706
	(0.029)	(1.220)	(0.664)	(1.175)
after3	0.025	-0.923	2.653	-3.520
	(0.036)	(1.809)	(1.558)	(1.999)
after4	0.073	0.756	2.108*	-1.227
	(0.041)	(1.432)	(0.936)	(1.320)
after5	0.089*	0.711	1.789	-1.012
	(0.040)	(1.481)	(0.948)	(1.313)
after6	0.076	0.539	2.195*	-1.438
	(0.043)	(1.334)	(0.981)	(1.288)
N	42334	33687	33813	33687

Standard errors in parentheses, clustered at the village (CCPP) level
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 6: Home business outcomes

	(1)	(2)
	Has Home Business	Profit
before3	-0.027	-0.019
	(0.019)	(0.034)
before2	-0.034	0.024
	(0.025)	(0.124)
before1	0.017	0.025
	(0.018)	(0.051)
after1	0.040*	0.013
	(0.019)	(0.044)
after2	0.054	0.071
	(0.028)	(0.113)
after3	0.021	0.202
	(0.030)	(0.233)
after4	0.031	0.112
	(0.034)	(0.123)
after5	0.098**	0.154
	(0.038)	(0.132)
after6	0.073	0.169
	(0.039)	(0.132)
N	42334	40817

Standard errors in parentheses, clustered at the village (CCPP) level

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 7: Robustness check: migration

	(1)
	Born in District
before3	0.005
	(0.015)
before2	0.025
	(0.021)
before1	-0.002
	(0.017)
after1	0.004
	(0.017)
after2	0.012
	(0.024)
after3	0.014
	(0.026)
after4	-0.040
	(0.030)
after5	-0.019
	(0.030)
after6	-0.036
	(0.030)
N	187378

Standard errors in parentheses, clustered at the village (CCPP) level
* p<0.05, ** p<0.01, *** p<0.001

Table 8: Heterogeneous effects: mobile phone ownership

				Log Expenditures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log Income	Has Assets	Log Assets	Total	Food	Non-Food	Durable
after1	-0.057	-0.028	-0.042	0.020	0.036	0.010	-0.221*
	(0.055)	(0.024)	(0.084)	(0.050)	(0.050)	(0.066)	(0.104)
after2	0.066	-0.054	0.064	0.075	0.116*	0.065	-0.103
	(0.074)	(0.032)	(0.123)	(0.059)	(0.058)	(0.081)	(0.136)
after3	0.006	-0.043	-0.004	0.057	0.057	0.094	-0.090
	(0.088)	(0.029)	(0.132)	(0.066)	(0.065)	(0.092)	(0.172)
after4	0.068	-0.093	-0.185	0.065	0.029	0.033	0.098
	(0.093)	(0.057)	(0.176)	(0.079)	(0.077)	(0.106)	(0.165)
after5	0.165	-0.062	0.248	0.339***	0.328***	0.206	0.160
	(0.115)	(0.047)	(0.168)	(0.085)	(0.089)	(0.108)	(0.177)
after6	0.118	-0.070	0.031	0.298***	0.252**	0.190	0.142
	(0.102)	(0.041)	(0.178)	(0.082)	(0.083)	(0.108)	(0.192)
own_after1	0.802***	0.104**	1.430***	0.728***	0.528***	0.976***	0.866***
	(0.104)	(0.032)	(0.184)	(0.095)	(0.095)	(0.117)	(0.238)
own_after2	0.710***	0.150***	0.973***	0.469***	0.295***	0.593***	0.893***
	(0.095)	(0.026)	(0.204)	(0.090)	(0.079)	(0.094)	(0.185)
own_after3	0.514***	0.076*	1.280***	0.424***	0.467***	0.504***	0.597*
	(0.123)	(0.034)	(0.182)	(0.120)	(0.091)	(0.147)	(0.264)
own_after4	0.464***	0.093	0.956***	0.496***	0.386***	0.641***	0.674***
	(0.112)	(0.057)	(0.223)	(0.092)	(0.087)	(0.121)	(0.172)
own_after5	0.617***	0.168***	0.534*	0.449***	0.350***	0.535**	0.539*
	(0.126)	(0.041)	(0.227)	(0.101)	(0.101)	(0.168)	(0.240)
own_after6	0.590***	0.092**	1.184***	0.419***	0.327***	0.480***	0.588***
	(0.089)	(0.028)	(0.187)	(0.077)	(0.086)	(0.089)	(0.145)
N	40093	42335	28508	42148	41248	41850	32689

Standard errors in parentheses, clustered at the village (CCPP) level
* $p<0.05$, ** $p<0.01$, *** $p<0.001$