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The Power of Information

The Impact of Mobile Phones on Farmers' Welfare in the Philippines

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Abstract

The authors explore the impact of access to information on poor farmers' consumption. The analysis combines spatially coded data on mobile phone coverage with household panel data on farmers from some of the poorest areas of the Philippines. Both the ordinary least squares and instrumental variable estimates indicate that purchasing a mobile phone has a large, positive impact on the household-level growth rate of per capita consumption. Estimates range from 11 to 17 percent, depending on the sample and the specification chosen. The authors perform a range of reliability tests, the results of which all suggest that the instruments are valid. They also present evidence consistent with the argument that easier access to information allows farmers to strike better price deals within their existing trading relationships and to make better choices in terms of where they choose to sell their goods.

This paper—a product of the Social Development Department, Sustainable Development Network—is part of a larger effort in the department to analyze how increased information flow affect household welfare. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at jlabonne@worldbank.org and rchase@worldbank.org.

The Power of Information:

The Impact of Mobile Phones on Farmers' Welfare in the Philippines [1]

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1. Introduction

Farmer welfare in developing countries depends directly on the price at which they sell their produce (Jensen, 2007). Bargaining theory indicates that asymmetric information on the prevailing price between farmers and traders is detrimental to farmer welfare. Providing price information to farmers could be beneficial by increasing their bargaining power when they negotiate with traders (Jaleta and Gardebroek, 2007). They should get better prices for their produce, which, in turn, should translate into higher consumption. Press reports indicate that Filipinos farmers use mobile phones as a marketing tool and to get price information. For example, Arnold (2001) mentions that "vegetable farmers (…) were using mobile phones to market their produce in Manila."

In this paper, we explore the impact of information technologies on farmer welfare in developing countries. In particular, we assess whether the growth rate of per capita consumption is larger for farmers purchasing a mobile phone. We also discuss channels through which those impacts might materialize.

The paper makes important contributions to on-going debates concerning the impact of information technology on welfare in developing countries. First, while the literature has so far focused on the impact of information technologies on the functioning of markets, we assess their impacts on farmer welfare directly. We do so combining spatially coded data on mobile phone coverage with household panel data collected from farmers in 135 villages in some of the poorest areas of the Philippines in 2003 and 2006. Thus, we can assess if *changes* in consumption can be attributed to mobile phone ownership, while controlling for baseline consumption, changes in household characteristics and shocks experienced by the household in the 2003-2006 period.

Second, we allow for selection on unobservables, as the decision to purchase a mobile phone is likely to be endogenous (*i.e.*, it can be difficult to discern whether buying a mobile phone generates increased consumption or increased consumption opportunities lead households to buy a mobile phone). Our instrumental variables (IV) strategy combines information on mobile phone availability at the village-level and the highest education level achieved among children in the household, arguing that young people within the household who might learn about this new technology from friends in school and whose educational attainment will have plausibly little influence on household consumption, are likely to be instrumental in terms of convincing their elders to purchase a mobile phone. Specifically, we interact a variable equal to the number of years (in 2006) since mobile phone service became available in the village with the highest education levels achieved among children in school in 2003 in the household. We provide strong evidence that our instruments are statistically valid. We can reject the hypothesis that our instruments are weak and provide evidence consistent with the exclusion restriction, which increases our confidence that our estimation strategy is valid. For example, using our IV strategy we show that, as expected given our argument that mobile phone access affects the bargaining power of those farmers that trade their produce, purchasing a mobile phone has no impact on the growth rate of per capita consumption for subsistence farmers. Indeed, as they are not engaged in market activities they cannot take advantage of improved marketing practices that mobile phones allow. This suggests that our instruments do not have any direct impact on the growth rate of per capita consumption.

Our results indicate that farmers purchasing a mobile phone experienced larger growth rate of per capita consumption over the 2003-2006 period. Estimates range from 11 percent to 17 percent depending on the sample and the specification chosen. This suggests that information technologies can contribute to poverty reduction in developing countries. This result is robust to the inclusion of a number of control variables (including measures of both positive and negative shocks) and to allowing for selection on unobservables. It is also robust to the exclusion of all farmers who owned a mobile phone in 2003 and to alternative specifications. Results presented in this paper are consistent with the argument that the impact we measure is driven by farmers being able to strike better price deals within their existing trader relationships and to make better choices in their target markets.

The paper is organized as follows. Section 2 briefly reviews the literature and discusses our hypotheses. Section 3 describes the dataset. The estimation strategy is presented in Section 4 and results are discussed in Section 5. Potential channels through the impacts materialized are presented in Section 6 and Section 7 concludes.

2. Literature and Hypotheses

Emerging evidence indicates that information technologies can promote growth and increase welfare. Using cross-country data, Roller and Waverman (2001) argue that improvements in telecommunications have a positive and significant impact on growth. More forcefully, Jensen (2007), in a study of the fisheries sector in south India, finds that the adoption of mobile phones increased both consumer and producer welfare. For example, fishermen profits went up about 10 percent after the introduction of mobile phone service. Aker (2008) demonstrates that the introduction of mobile phones led to significant reduction in price dispersion among grain markets in Niger. In addition, Goyal (2008) shows that providing wholesale price information has a positive impact on the price received by producers. Finally, Klonner and Nolen (2008) show that in South Africa cell phone network roll-out has a positive impact on household income. We improve on the literature by assessing the household-level welfare impacts of purchasing a mobile phone.

As indicated in Figures 1 and 2, mobile phone coverage has spread quickly in the Philippines. This has been accompanied by a robust growth in mobile phone ownership. While the share of the population with a mobile phone was 15.6 percent in 2001, it rose to 27.7 by 2003 and reached 49.7 percent by 2006. In neighboring Indonesia, the figures were respectively 3.1 percent, 8.6 percent and 28.6 percent.[2]

[2] World Development Indicators (2008) Accessed on 05/12/2008
http://ddp-ext.worldbank.org/ext/DDPQQ/member.do?method=getMembers

Functions performed by mobile phones also increased rapidly from simple text messaging to financial transactions. For example, some operators have introduced services allowing individuals to transfer money from a bank account to a mobile phone. By mid-2007, about 5.5 million Filipinos were using such services (Forbes, 2007). In addition, some of those services are available to international migrants who can send remittances directly to their relatives via their mobile phones. Money is immediately available for withdrawal at designated locations

Insights from research on asymmetric information indicate that traders, having better market information, will be at an advantage when negotiating with farmers over the price of their produce. The introduction and adoption of mobile phones might increase farmer bargaining power, however. Indeed, farmers can use their mobile phone either to get price information from friends and relatives or to get a quote from another trader (thus reducing the uncertainty regarding the trader's willingness-to-pay for their produce).

Further, the adoption of mobile phones could impact farmers' decision to travel to market rather than to sell at farm-gate. Indeed, without local market information, farmers might be reluctant to take the costly trip to markets to sell their goods. This would change once farmers use mobile phones. However, as pointed out by Fafchamps and Vargas Hill (2005), farmers able to pay to transport their goods to market will benefit more from such opportunities. Overall, this indicates that farmer income will increase after adopting mobile phones, which should translate into higher consumption levels.

3. The Data

This study uses spatially coded data on mobile phone coverage together with a household panel dataset that was collected in the Philippines in the fall of 2003 and 2006 for the impact evaluation of a participatory development project. The GSM coverage maps (cf. Figures 1 and 2) are a compilation of coverage information provided by network operators. Coverage areas are aggregate, reflecting the combined coverage of operators, and do not include information on quality of service. We have access to the databases for 2002, 2003, 2004 and 2006.

The original household sample covers 2,400 households in 135 villages in 16 of the poorest municipalities of the Philippines (Chase and Holmemo, 2005). The second survey was fielded in the same 135 villages and the survey team managed to re-interview 2,092 households (about 87.2 percent of the original number of households). In this paper, we use data on the households which were interviewed in both rounds and were engaged in farming activities during both periods. We focus on farmers, given that we have identified clear channels through which mobile phones could positively affect their welfare.

The panel dataset contains detailed information on mobile phone ownership (*mobile*), poverty status, consumption, shocks experienced, gifts received from friends and relatives, and migration patterns. We have information on the years of education of the household head (*Edu Head*), of his/her spouse (*Edu Spouse*) and of the most educated household member apart from the head and his/her spouse (*Max Edu*), on the number of household members (*HH Size*), on the number of household members above the age of sixty (*Above Sixty*) and under the age of five (*Under Five*), on the age of the household head (*Age Head*) and his/her spouse (*Age Spouse*), and on whether the household owns land for purposes other than residence (*Own Land*).

Using the data available, we construct a measure of per capita monthly consumption (*pc cons*). For each household member above five years of age, we have detailed information on whether they were working in the three months prior to the survey and, if so, in which sector. We can thus calculate the number of household members working in the farm and in the non-farm sector (*Working Farm* and *Working non-Farm*).

During the second survey, detailed information on migration patterns was collected. We use this information to generate, for each original household for which at least one original member still lived in the village, a dummy equal to one if at least one household member had migrated during the three-year period (*migrant*). We also have information on the number and types of shocks faced by the households during the 2003-2006 period. We create two dummies equal to one if either a household member suffered from a serious illness between the two surveys (*health*) or if a household member died over the same period (*death*).

Descriptive statistics are available in Table 1. Mobile phone ownership is not as widespread in our sample communities as it is in the country as a whole. The proportion of farmers who owned a mobile phone was 7.2 percent in 2003 and it increased to 35.0 percent in 2006. Given that our data purposefully sampled the poorest areas of the Philippines, this is not surprising.

4. Estimation Strategy

4.1. Basic setup

We want to estimate the impact of mobile phone ownership on consumption patterns. Let $\Delta Ln(C_{ij})$ be the change in household *i*'s (log) per capita consumption between t=0 (2003) and t=1 (2006), *j* will index villages. We assume that the growth rate of per capita consumption is determined by:

$$\Delta Ln(C_{ij}) = \alpha * Ln(C_{ij0}) + \beta * M_{ij} + \delta * \Delta X_{ij} + \gamma * S_{ij} + v_j + w_{ij} \qquad (1)$$

where α, β, δ and γ are coefficients to be estimated, $Ln(C_{ij0})$ is household i's (log) per capita consumption at t=0, M_{ij} is a variable equal to one if household *i* in village *j* did not own a mobile phone in 2003 and purchased one during the 2003-2006 period and zero otherwise, ΔX_{ij} is the change in a vector of control variables that vary across households and time, S_{ij} is a vector of shocks (positive and negative) experienced by household *i* between t=0 and t=1, v_j is an effect common to all households in village *j* and, w_{ij} is the usual idiosyncratic error term. We will estimate equation (1) through OLS, include village dummies (in order to account for v_j) and compute standard-errors robust to an arbitrary variance structure within villages. In addition, to assess the robustness of our results, we will also estimate equation (1) on the subsample of farmers who did not own a mobile phone in 2003. \

4.2. Selection on Unobservables

The decision to purchase a mobile phone might be correlated with unobservable household characteristics (w_{ij}) which would lead to biased estimates. We deal with this problem by using instrumental variables (IV). As usual, we need instruments that are correlated with the decision to purchase a mobile phone but uncorrelated with w_{ij} (other than through their impact on the decision to purchase a mobile phone). We will combine information on mobile phone availability at the village-level and the highest education levels achieved among children in school in 2003 in the household arguing that mobile phone adoption is driven mostly by the educated younger generation within households.

Using data from the GSM coverage dataset described above, we create a variable capturing the supply of mobile phone service at the village-level. This variable is equal to the number of years (in 2006) since mobile phone service became available in the village. This variable, which is correlated with the decision to purchase a mobile phone, is unlikely to be correlated with w_{ij}. However, this variable is constant within villages and we need an instrument with household-level variation. We create such a variable by interacting it with the highest education levels achieved among children in school in 2003 in the household. The rationale is that more educated individuals are more likely to hear about and to adopt new technologies such as mobile phones. Moreover, young people within the household, whom educational attainment will have plausibly little influence on household consumption, are likely to be instrumental in terms of convincing their elders to purchase a mobile phone. We exclude older individuals in the household as their education levels are likely to influence consumption patterns directly which would violate our exclusion restriction. We use the standard 2SLS estimator.[3]

Instrumental variable estimates can be biased when instruments are weak, that is when the endogenous regressor is only weakly correlated with the instruments. We test whether our instrument set is weak against the alternative hypothesis that it is strong using the test proposed by Stock and Yogo (2005). This test uses the Cragg-Donald statistics (equivalent to a first-stage F-statistic when there is only one regressor). In all regressions we can reject the null hypothesis that our instrument is weak: this provides evidence of the validity of our identification strategy.

5. Access to Information and Household Consumption

5.1. Basic Results

We now assess the impact of purchasing a mobile phone on the growth rate of per capita consumption. We exclude all communication items (*e.g.,* phone bills, etc.) from our measure of consumption. In our baseline results, the vector ΔX_{ij} includes the 2003-2006 change in household size, the number of household members under the age of five, the number of household members above the age of sixty, the age of both the household head and his/her spouse, and in a dummy equal to one if the household owns land for purposes other than residence. We start with municipal dummies rather than village dummies. We include both the variable capturing mobile phone availability and its interaction with the highest educational level achieved in the household by someone other than the head and his/her spouse (in 2003). Results are reported in Panel A of Table 2.

Purchasing a mobile phone is associated with greater increases in per capita consumption (excluding all communication related expenses). Specifically, it is associated with a 15.0 percent increase in the growth rate of per capita consumption. As discussed above, in addition to simple OLS estimates we also present IV estimates. These are consistent with

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[3] As a robustness check, we also estimate equation (1) using the IV-LIML estimator. Those estimates are fully consistent with those presented in the paper. Results available upon request.

previous research (discussed above) which suggests that mobile phone ownership has a causal impact on per capita consumption. In this specification we use both our variable capturing the length of time since mobile phone service became available and the interaction term with the highest education levels in the household (apart from the head and his/her spouse). Our OLS and IV results are similar once we replace municipal dummies with village dummies. For example, our OLS estimate with village dummies indicates a 13.1 percent increase in the growth rate of per capita consumption.

We now include the 2003-2006 change in educational level of the household head and his/her spouse in ΔX_{ij} to see whether much of the observed increase in consumption results from changes in education. Results are reported in Panel B of Table 2. Including these education variables has almost no impact on our estimates either with municipal or village dummies. Point estimates are 0.148 with municipal dummies and 0.129 with village dummies.

We now include the 2003-2006 change in the number of household members working in the non-farm sector and in the number of household members working in the farm sector in ΔX_{ij}. The vector S_{ij} includes a dummy equal to one if a household member migrated over the period, a dummy equal to one if a household member died over the period, and a dummy equal to one if a household member suffered a serious illness over the period. Results are reported in Panel C of Table 2. Our estimates are comparable to those obtained previously in both size and significance levels. Point estimates reflect a 14.0 percent increase in consumption with municipal dummies and a 12.4 percent increase with village dummies.

As indicated above, we also estimate equation (1) for the sample of farmers who did not own a mobile phone in 2003. Results are presented in Table 3. Our estimates are consistent with those discussed earlier. Point estimates range from 15.3 percent to 17.7 percent.

5.2. Potential Concerns

We now address potential concerns with our results. First, while we exclude all communication-related items from our measure of consumption growth, our results could be capturing the small consumption increase associated with purchasing a mobile phone. We therefore re-estimate equation (1) while excluding all purchases of durable goods from our consumption variable. Results are presented in Panel A of Table 4. Our estimates are similar to those obtained previously.

Second, changes in consumption might be influenced by baseline education levels rather than changes in education levels. As a result, we re-estimate equation (1) while replacing the changes in household head (and his/her spouse) education levels with their 2003 values. Results are reported in Panel B of Table 4. Our estimates are consistent with those obtained previously with point estimates of 12.0 percent with the full sample and of 15.1 percent once we exclude farmers who owned a mobile phone in 2003.

Third, our instrument might be capturing the age of the children with the highest education in the household. As a result, we re-estimate equation (1) including the age of the children with the highest level of education (our instrument). Results are presented in Panel C of Table 4. The only difference with previous estimates is that for the full sample our OLS estimate is now marginally not significant.

Finally, as indicated above, the data were collected for the purpose of an impact evaluation of a community-driven development project (Chase and Holmemo, 2005). If households who purchased a mobile phone also benefited from the project, our results could capture project impacts rather than benefits associated with a mobile phone. Thus, we re-estimate equation (1) but exclude all villages in which the project was implemented. Results are presented in Panel D of Table 4. Even after excluding this set of villages, mobile phone ownership still has a positive impact on per capita consumption. The point estimate is now larger than before, suggesting that the impact is higher in non-project areas. As municipalities selected to participate in the project were poorer than the control municipalities (Chase and Holmemo, 2005), this suggests that the impact of mobile phones is larger in areas better integrated into markets.

5.3. Assessing the validity of our exclusion restrictions

The validity of our IV estimates relies on the assumption that, once we control for all the other covariates, our instrument does not have any direct impact on changes in consumption. We now provide further evidence that our estimation strategy is valid.

We compare our IV estimates for subsistence and non-subsistence farmers. We expect the positive impact of mobile phones to materialize through improved marketing practices (*i.e.*, that farmers use cell phones to get improved price information when they sell their produce). As a result, subsistence farmers should not benefit from access to mobile phones. Finding a positive impact on the subsample of subsistence farmers would cast serious doubt on the validity of our IV strategy as this would suggest that our instrument has a direct positive impact on consumption. Consistent with the argument that the decision to purchase a mobile phone is endogenous, in both cases our OLS estimates are significant and positive.

For each of our consumption variables used in the analysis and using our IV strategy, we find a positive impact of mobile phones on per capita consumption for the subsample of non-subsistence farmers and no impact for the subsample of subsistence farmers. Results are presented in Panels A and B of Table 5. Our results are consistent with the argument that our instrument does not have a direct impact on the growth rate of per capita consumption. This provides strong support for the argument that our exclusion restriction is correct.

As before, we also run the reliability tests with the sample of farmers who did not own a mobile phone in 2003. Results are presented in Panels C and D of Table 5. In both cases, our results are consistent with those obtained above.

6. Potential Channels

So far, our results indicate that access to mobile phones has a positive impact on the growth rate of per capita household consumption. We do not explain the mechanism through which this impact materializes, however. We attempt to do so in this section.

As discussed above, easier access to information might increase farmer bargaining power when negotiating with traders. They should thus get better prices for their produce. Ideally, we would test this using transaction-level data on the price at which farmers sell their crops. Unfortunately, such data is unavailable. As a proxy, we assess whether access to a mobile phone has a positive impact on the relations between farmers and traders. Specifically, we re-estimate equation (1) but replace our consumption growth measure with the change in a measure of self-reported trust in traders.[4] Results are reported in Panel A of Table 6.

Owning a mobile phone is associated with an increase in trust in traders. While not a direct proof that farmers with access to mobile phones get better prices from traders, this result is consistent with the argument that farmers get a greater share of the surplus once they have a mobile phone. At least, this suggests that farmers with mobile phones are more likely to have better information on market prices and thus potentially more likely to engage in beneficial exchanges with traders.

Our measure of trust is self-reported and, thus, our results might capture 'mood effects' associated with owning such a high status good rather than the actual impact of owning a mobile phone. As a result, we re-estimate our equation but substitute our measure of trust in traders with a measure of generalized trust. If the impact of mobile phones on trust in traders were merely capturing 'mood effects', we should observe a similar result on generalized trust. Results are presented in Panel B of Table 6. Owning a mobile phone is

[4] Our measure of trust is the answer to the question "on a scale from 1 to 5, where 1 means a very small extent and 5 means a very great extent, how much do you trust traders" Individuals answering 5 or 4 are considered trusting and others are considered non-trusting.

not associated with a positive change in generalized trust. This appears to rule out concerns about mood effects.

Another potential benefit of better market information is to increase the likelihood that farmers will make better choices on target traders/markets. To test this, we assess if mobile phone ownership is associated with an increase in the frequency with which they go to municipal markets. Indeed, under the likely assumption that price uncertainty prevents farmers from travelling to markets to sell their goods, we should expect that better price information would lead farmers to travel to markets more frequently. As before, we re-estimate equation (1) but substitute our consumption variable with the number of trips to the municipal market taken during the month prior to the survey. Results are available in Panel C of Table 6. Owning a mobile phone is associated with an increase in the number of trips taken to the municipal market. Further, households able to pay for transporting their goods to market might be better able to take advantage of those new opportunities (Fafchamps and Vargas Hill 2005). As a result, we interact our mobile phone dummy with a dummy equal to one if the household owned a motorcycle in 2003. The interaction term is positive and significant. This is consistent with the argument that access to better information allows households with access to transportation to increase the range of markets at which they sell their produce.

7. Conclusion

This paper analyzed the role of information on farmers' consumption. Combining spatially coded data on mobile phone coverage with panel data from farmers in rural areas of the Philippines, we show that purchasing a mobile phone has a large positive impact on the growth rate of per capita consumption. Estimates range from 11 percent to 17 percent depending on the sample and the specification chosen. This result is robust to the inclusion of a number of control variables and to allowing for selection on unobservables. We also include independent variables capturing both positive and negative shocks. Further, we present evidence consistent with the argument that access to better information allows farmers to strike better price deals within their existing trading relationships and to make better choices in their markets.

Our results are only a first step in understanding how information technologies impact household welfare. We see at least three areas where more research would be helpful. First, using transaction-level data on traders and farmers (with and without mobile phones) would allow us to test whether access to price information increases farmer bargaining power when dealing with traders. Second, it would be valuable to test whether better access to market information has a positive impact on farmers' crop choices. Indeed, it could potentially allow farmers to diversify their crop mix. Finally, it would be interesting to compare those impacts for farmers with a different product mix (*e.g.,* perishable and nonperishable products). In light of the results discussed in this paper, it is possible that farmers producing perishable products (*i.e.,* products more likely to experience large day-to-day price variations) will benefit more from mobile phone access than farmers producing nonperishable products. This is left for further research.

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Tables

Table 1 – Descriptive Statistics

	2003			2006		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Mobile	1231	0.07	(0.47)	1231	0.35	(0.26)
Wealth	1231	-0.55	(2.31)	1231	0.43	(2.81)
Education (Head)	1231	5.42	(3.06)	1212	6.00	(3.20)
Education (Spouse)	1056	6.28	(3.03)	1008	6.54	(2.98)
Working Farm	1231	1.73	(1.16)	1231	1.77	(1.17)
Working Non Farm	1231	0.36	(0.66)	1231	0.40	(0.70)
HH Size	1231	5.29	(2.19)	1231	5.23	(2.20)
Age Head	1231	47.29	(13.66)	1231	49.57	(13.20)
Above Sixty	1231	0.36	(0.66)	1231	0.42	(0.70)
Under Five	1231	0.83	(0.97)	1231	0.72	(0.95)
Age Spouse	1231	36.25	(18.63)	1231	37.01	(20.24)
Own Land	1231	0.39	(0.49)	1231	0.54	(0.50)
Log pc cons. (exc. Communication)	1231	6.62	(0.59)	1231	7.08	(0.59)
Trust Trader	1217	0.61	(0.49)	1231	0.60	(0.49)
Monthly trips	1231	3.70	(6.50)	1230	3.61	(6.02)
Migrant				1231	0.35	(0.48)
Death				1231	0.09	(0.28)
Health				1231	0.19	(0.39)

Table 2- Mobile Phone Purchase and Growth Rate of per capita Consumption

	(1) OLS	(2) IV-2SLS	(3) OLS	(4) IV-2SLS
Panel A : Basic set of controls				
Mobile	0.150	0.452	0.131	0.378
	(0.032)***	(0.155)***	(0.036)***	(0.150)**
F-Stat for IV		26.1		43.2
Dummies	Municipal	Municipal	Village	Village
Obs.	959	669	959	669
R-squared	0.35		0.43	
Panel B : Basic set of controls and education variables				
Mobile	0.148	0.446	0.129	0.368
	(0.031)***	(0.157)***	(0.035)***	(0.151)**
F-Stat for IV		25.1		42.5
Dummies	Municipal	Municipal	Village	Village
Obs.	959	669	959	669
R-squared	0.35		0.43	
Panel C : Basic set of controls education variables and shocks				
Mobile	0.140	0.401	0.124	0.357
	(0.032)***	(0.167)**	(0.036)***	(0.169)**
F-Stat for IV		22.0		35.2
Dummies	Municipal	Municipal	Village	Village
Obs.	959	669	959	669
R-squared	0.36		0.44	

Note: **Results from OLS (Column 1 and 3) and IV-2SLS regressions (Column 2 and 4)** The dependent variable is the household-level change (2003-2006) in the (log) per capita consumption (exc. communication). Each cell is the coefficient on our mobile phone variable from a different regression. Instrument set is *Cell Availability* and *Cell Availability *Max Education Children 6-20 (2003)* . The standard errors (in parentheses) are Huber-corrected and account for intra-village correlation. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Control Variables: All regressions include the baseline value of the outcome of interest, as well as the 2003-2006 change in household size, household head (and spouse) age, number of household members above sixty, number of household members under five and in a dummy indicating if the household owns land for purposes other than residence. We also include municipal dummies (Column 1 and 2) and village dummies (Column 3-4). In Panel B, we add to the control variables included in Panel A, the change in household head (and spouse) education levels (in years). In Panel C, we add to the control variables included in Panel B, a dummy equal to one if a household member migrated over the period, the change in the number of household members working in the farm sector, the change in the number of household members working in the non-farm sector, a dummy equal to one if a household member died over the period and, a dummy equal to one if a household member suffered a serious illness over the period.

Table 3- Mobile Phone Purchase and Growth Rate of per capita Consumption

	(1) OLS	(2) IV-2SLS	(3) OLS	(4) IV-2SLS
Panel A : Basic set of controls				
Mobile	0.177	0.440	0.154	0.383
	(0.032)***	(0.139)***	(0.037)***	(0.149)**
F-Stat for IV		39.5		54.2
Dummies	Municipal	Municipal	Village	Village
Obs.	892	621	892	621
R-squared	0.36		0.45	
Panel B : Basic set of controls and education variables				
Mobile	0.176	0.430	0.153	0.364
	(0.032)***	(0.142)***	(0.036)***	(0.150)**
F-Stat for IV		35.5		49.2
Dummies	Municipal	Municipal	Village	Village
Obs.	892	621	892	621
R-squared	0.36		0.45	
Panel C : Basic set of controls education variables and shocks				
Mobile	0.173	0.408	0.156	0.365
	(0.032)***	(0.153)***	(0.036)***	(0.171)**
F-Stat for IV		30.1		41.4
Dummies	Municipal	Municipal	Village	Village
Obs.	892	621	892	621
R-squared	0.38		0.47	

Note: **Results from OLS (Column 1 and 3) and IV-2SLS regressions (Column 2 and 4)** The dependent variable is the household-level change (2003-2006) in the (log) per capita consumption (exc. communication). Each cell is the coefficient on our mobile phone variable from a different regression. Instrument set is *Cell Availability* and *Cell Availability *Max Education Children 6-20 (2003*) . The standard errors (in parentheses) are Huber-corrected and account for intra-village correlation. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Control Variables: All regressions include the baseline value of the outcome of interest, as well as the 2003-2006 change in household size, household head (and spouse) age, number of household members above sixty, number of household members under five and in a dummy indicating if the household owns land for purposes other than residence. We also include municipal dummies (Column 1 and 2) and village dummies (Column 3-4). In Panel B, we add to the control variables included in Panel A, the change in household head (and spouse) education levels (in years). In Panel C, we add to the control variables included in Panel B, a dummy equal to one if a household member migrated over the period, the change in the number of household members working in the farm sector, the change in the number of household members working in the non-farm sector, a dummy equal to one if a household member died over the period and, a dummy equal to one if a household member suffered a serious illness over the period.

Table 4 : Potential Concerns

	(1) OLS	(2) IV-2SLS	(3) OLS	(4) IV-2SLS
	Full Sample		Only farmers without mobile phone in 2003	
Panel A: Log pc consumption (exc. Communication and durable goods)				
Mobile	0.128	0.352	0.162	0.359
	(0.035)***	(0.170)**	(0.036)***	(0.168)**
F-Stat for IV		36.7		43.7
Obs.	953	665	888	618
R-squared	0.43		0.46	
Panel C : 2003 Edu Levels (instead of change)				
Mobile	0.120	0.349	0.151	0.387
	(0.035)***	(0.165)**	(0.036)***	(0.164)**
F-Stat for IV		36.2		49.3
Obs.	959	669	892	621
R-squared	0.44		0.47	
Panel B : Control Age Max020				
Mobile	0.071	0.391	0.115	0.426
	(0.049)	(0.173)**	(0.049)**	(0.178)**
F-Stat for IV		31.6		36.2
Obs.	669	669	621	621
R-squared	0.43		0.48	
Panel B: Log pc consumption (exc. Communication) – Excluding Project Areas				
Mobile	0.119	0.526	0.172	0.470
	(0.056)**	(0.224)**	(0.051)***	(0.206)**
F-Stat for IV		26.2		41.0
Obs.	416	296	381	273
R-squared	0.43		0.49	

Note: **Results from OLS (Column 1 and 3) and IV-2SLS regressions (Column 2 and 4)** The dependent variable is the household-level change (2003-2006) in the (log) consumption measure considered. Each cell is the coefficient on our mobile phone variable from a different regression. Instrument set is *Cell Availability* and *Cell Availability *Max Education Children 6-20 (2003)* . The standard errors (in parentheses) are Huber-corrected and account for intra-village correlation. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Control Variables: All regressions include the baseline value of the outcome of interest, village dummies as well as the 2003-2006 change in household size, household head (and spouse) age, number of household members above sixty, number of household members under five, household head (and spouse) education levels (in years), and the 2003-2006 change in a dummy indicating if the household owns land for purposes other than residence. We also include a dummy equal to one if a household member migrated over the period, the change in the number of household members working in the farm sector, the change in the number of household members working in the non-farm sector, a dummy equal to one if a household member died over the period and, a dummy equal to one if a household member suffered a serious illness over the period. In Panel C, we substitute the 2003-2006 change in household head (and spouse) education levels (in years) with the 2003 value of household head (and spouse) education levels (in years).

Sample: In Panel D, we exclude all villages in which the KALAHI-CIDSS project was being implemented.

Table 5 – Reliability Tests

	(1) OLS	(1) IV-2SLS	(1) OLS	(2) IV-2SLS
	Subsistence Farmers		Non-Subsistence Farmers	
Panel A: Log pc consumption (exc. Communication)				
Mobile	0.289	1.463	0.084	0.416
	(0.097)***	(1.074)	(0.048)*	(0.202)**
Village dummies	Yes	Yes	Yes	Yes
Obs.	282	199	676	470
R-squared	0.62		0.47	
Panel B: Log pc consumption (exc. Communication and durable goods)				
Mobile	0.277	1.486	0.093	0.422
	(0.094)***	(1.110)	(0.047)*	(0.209)**
Village dummies	Yes	Yes	Yes	Yes
Obs.	281	198	671	467
R-squared	0.62		0.46	
Panel C: Log pc consumption (exc. Communication) - No Cell in 2003				
Mobile	0.301	1.419	0.116	0.354
	(0.099)***	(0.899)	(0.050)**	(0.189)*
Village dummies	Yes	Yes	Yes	Yes
Obs.	271	191	620	430
R-squared	0.63		0.50	
Panel D: Log pc consumption (exc. Communication and durable goods) – No Cell in 2003				
Mobile	0.288	1.424	0.127	0.353
	(0.096)***	(0.893)	(0.049)**	(0.193)*
Village dummies	Yes	Yes	Yes	Yes
Obs.	270	190	617	428
R-squared	0.63		0.49	

Note: **Results from IV-2SLS regressions.** The dependent variable is the household-level change (2003-2006) in the (log) consumption measure considered. Each cell is the coefficient on our mobile phone variable from a different regression. Instrument set is *Cell Availability* and *Cell Availability *Max Education Children 6-20 (2003)* . The standard errors (in parentheses) are Huber-corrected and account for intra-village correlation. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Control Variables: All regressions include the baseline value of the outcome of interest, village dummies as well as the 2003-2006 change in household size, household head (and spouse) age, number of household members above sixty, number of household members under five, household head (and spouse) education levels (in years), and the 2003-2006 change in a dummy indicating if the household owns land for purposes other than residence. We also include a dummy equal to one if a household member migrated over the period, the change in the number of household members working in the farm sector, the change in the number of household members working in the non-farm sector, a dummy equal to one if a household member died over the period and, a dummy equal to one if a household member suffered a serious illness over the period.

Sample: Subsistence farmers only (Column 1-2). Non-subsistence farmers only (Column 3-4).

Table 6: Potential Channels

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
	Full Sample		Only farmers without mobile phone in 2003	
Panel A : Trust Traders				
Mobile	0.233		0.239	
	(0.089)***		(0.093)**	
Village Dummies	Yes		Yes	
Obs.	941		875	
R-squared	0.59		0.59	
Panel B : Generalized Trust				
Mobile	-0.149		-0.125	
	(0.058)**		(0.061)**	
Village Dummies	Yes		Yes	
Obs.	932		867	
R-squared	0.63		0.65	
Panel C : Monthly Trip to Municipal Markets				
Mobile	1.069	0.857	1.257	0.924
	(0.429)**	(0.392)**	(0.419)***	(0.399)**
Mobile * Motorcycle (2003)		0.402		4.975
		(2.563)		(1.935)**
Village Dummies	Yes	Yes	Yes	Yes
Obs.	956	956	889	889
R-squared	0.53	0.55	0.52	0.53

Note: **Results from OLS regressions.** The dependent variable is the household-level change (2003-2006) in the variable considered. Each cell is the coefficient on our mobile phone variable from a different regression. The standard errors (in parentheses) are Huber-corrected and account for intra-village correlation. * denotes significance at the 10%, ** at the 5% and, *** at the 1% level.

Control Variables: All regressions include the baseline value of the outcome of interest, village dummies as well as the 2003-2006 change in household size, household head (and spouse) age, number of household members above sixty, number of household members under five, household head (and spouse) education levels (in years) , and the 2003-2006 change in a dummy indicating if the household owns land for purposes other than residence. We also include a dummy equal to one if a household member migrated over the period, the change in the number of household members working in the farm sector, the change in the number of household members working in the non-farm sector, a dummy equal to one if a household member died over the period and, a dummy equal to one if a household member suffered a serious illness over the period. . In Columns 2, 4 and 6, we also include a dummy equal to one if the household owned a motorcycle in 2003.

Figures

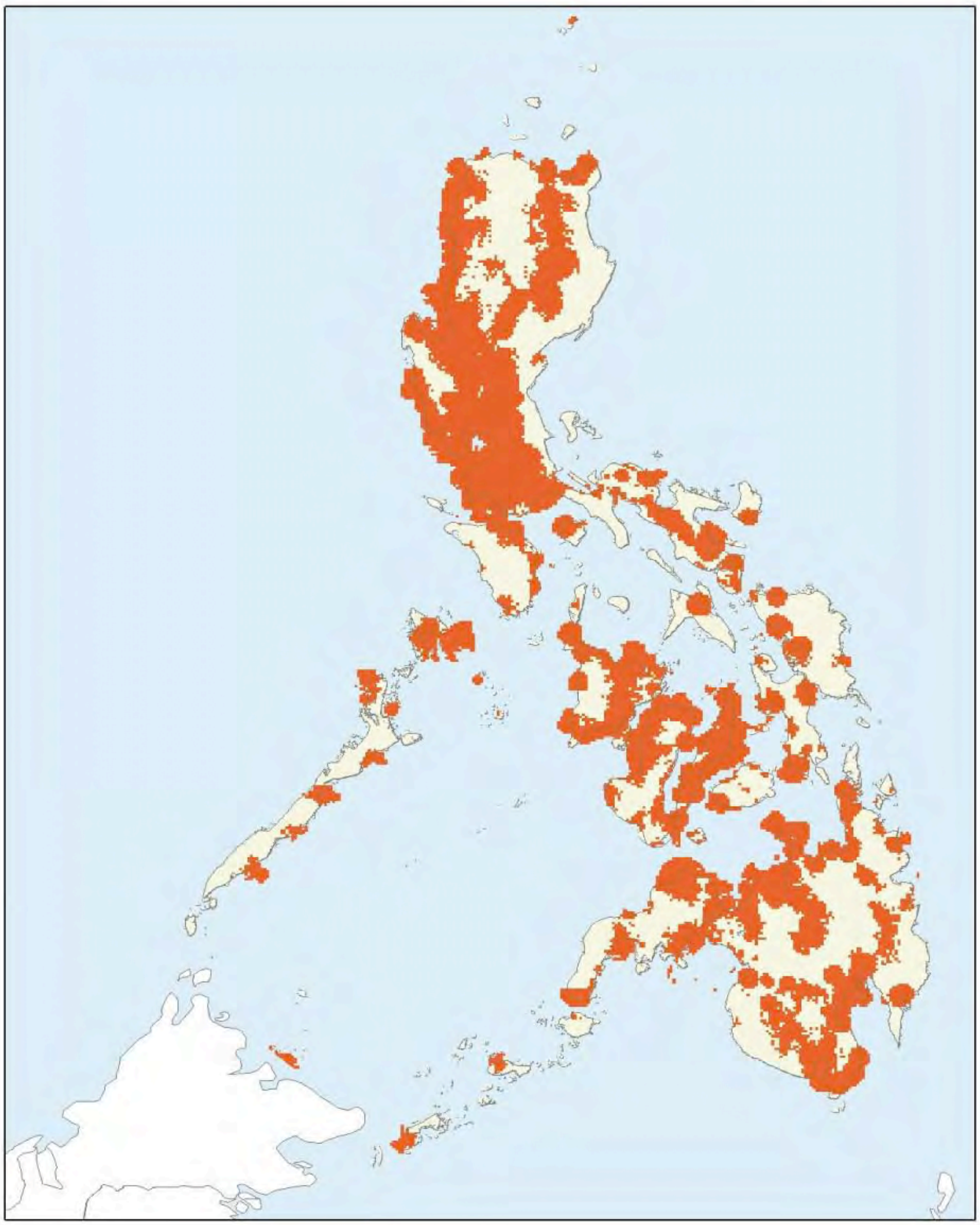

Figure 1: Mobile Phone Coverage in the Philippines in 2002

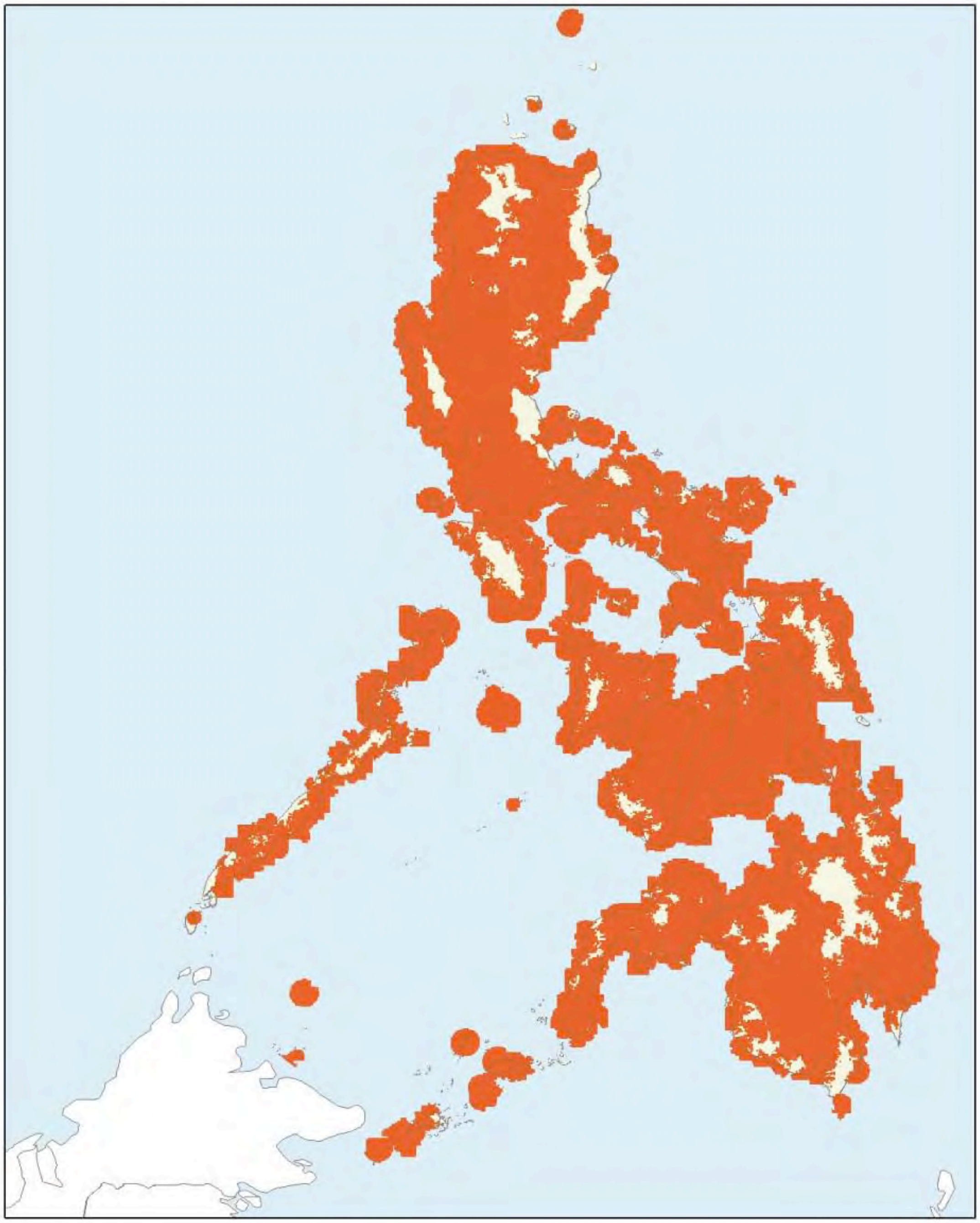

Figure 2: Mobile Phone Coverage in the Philippines in 2006