IDB WORKING PAPER SERIES No. IDB-WP-454

Information and Communication Technology, Agricultural Profitability, and Child Labor in Rural Peru

Diether W. Beuermann

October 2013

Inter-American Development Bank
Country Department Caribbean

Information and Communication Technology, Agricultural Profitability, and Child Labor in Rural Peru

Diether W. Beuermann

Inter-American Development Bank

Inter-American Development Bank

2013

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Beuermann, Diether W.
Information and communication technology, agricultural profitability, and child labor in rural Peru / Diether W. Beuermann.
p. cm. (IDB working paper series ; 454)
Includes bibliographical references.
1. Agriculture—Information technology—Peru. 2. Child labor—Peru. I. Inter-American Development Bank. Country Department Caribbean Group. II. Title. III. Series.
IDB-WP-454

http://www.iadb.org

1300 New York Ave. NW
Washington, DC 20577
dietherbe@iadb.org

Abstract

We estimate the impact of access to information and communication technology on agricultural profitability and child labor among isolated villages in rural Peru. We exploit the timing of an intervention that provided at least one public (satellite) payphone to 6,296 villages that did not previously have communication services. Using a village level panel, we show that profitability increased by 19.7 percent. Moreover, this income shock translated into a reduction in the likelihood of child market and agricultural work of 14 and nine percentage points respectively. Overall, the evidence suggests a dominant income effect in the utilization of child labor.

JEL classifications: O1, O3, Q1
Keywords: Information and Communication Technologies, Peru, Child Labor

1. Introduction

Economic theory emphasizes the importance of information for the efficiency of markets (Stigler, 1961; Brown & Goolsbee, 2002). Accordingly, reductions in information search costs are expected to enhance market effectiveness. Advances in information and communication technology (ICT) have made information transmission extremely cheap in developed societies. However, in the context of isolated communities in developing countries, ICT are still far from being universally available. Therefore, interventions providing new access to ICT in such societies provide an ideal opportunity to assess the impact of improved information accessibility on market performance. Furthermore, if market effectiveness is improved with new ICT, it becomes interesting to assess how this improved market performance influences household decisions such as the utilization of child labor. Accordingly, the purpose of this paper is to shed light on how the introduction of payphones among rural villages in Peru affected agricultural profitability and the utilization child labor.

Previous literature has studied the effects of ICT using the introduction of cell phone coverage. Jensen (2007) analyzed the impact of cell phones introduction among fishermen in the Indian state of Kerala. The results show that the adoption of mobile phones was associated with a dramatic reduction in price dispersion across markets, the complete elimination of waste, and near-perfect adherence to the law of one price. In the same vein, Aker (2010) studied the effects of cell phone introduction in Niger. She focuses on grain markets and suggests that cell phones reduced price dispersion across markets by 6.4 percent and intra-annual price variation by 12 percent. Furthermore, the study finds greater impacts in market pairs that are farther away and for those with lower road quality. The study suggests that the main mechanism by which cell phones generate these outcomes is a reduction in search costs. Traders who operate in markets with cell phone coverage search over a greater number of markets and sell in more markets, thereby reducing price dispersion.

Goyal (2010) provided evidence regarding the effects of internet kiosks placement among rural districts in the Indian state of Madhya Pradesh. These kiosks provided real time information of soybean market prices to farmers. The study shows that the kiosks caused an increase of 1.7 percent in the monthly mode price of soy. This result supports the theoretical prediction that the availability of price information to farmers increases the competitiveness of traders in local output markets, leading to an increase in the price of soybean in the intervened districts.

The intervention studied here was carried out by the Peruvian Fund for Investments in Telecommunications (FITEL), which provided at least one public (satellite) payphone, between years 2001 and 2004, to each of the 6,296 targeted villages situated across rural Peru. None of these villages had any kind of phone services (either fixed lines or cell coverage) prior to the intervention, so these payphones were the first opportunity for villagers to communicate with the rest of the country without having to physically travel or use the mail. According to FITEL's documents, the intervention reduced the average distance from any rural village in Peru to the nearest communication point from 60 to five kilometers.[1] I exploit differences in the timing of the intervention across villages to identify the impacts of payphones on agricultural profitability and the utilization of child labor, after showing that these differences in timing were orthogonal to the baseline levels of the outcomes.

It is worth noting that this intervention differs from the previous studies in that it involves public (satellite) payphones rather than cell phones or internet kiosks. This intervention occurred in places where neither cell phones nor fixed line phones were available. The treated villages were located in zones where cell phone coverage was technically and economically unfeasible. The satellite technology implemented did not require villages to posses fixed lines or electrical supply in order to enjoy the service. Therefore, phone placement only followed the criteria of being provided to villages without prior access to ICT. This coupled with differences in timing for phone placement that were uncorrelated with baseline characteristics, allows us to identify the impacts of interest using a unique panel of intervened villages.

Previous studies regarding the economic effects of ICT concentrate on market outcomes, with a specific focus on price dispersion, market performance and profitability. However, none directly assess whether the potentially increased profitability may affect the utilization of child labor which is very common in rural Peru. If ICT affects agricultural profitability, expected effects on child labor utilization are ambiguous. On the one hand, the substitution effect implies that the opportunity cost of time for a child that is not working becomes higher. Therefore, this effect suggests an increased utilization of child labor. However, on the other hand, an increased income enjoyed by the household suggests that the utilization of child labor will decrease and, therefore, the child will devote more time to activities representing normal goods for the household (such as leisure or schooling).

[1] This refers to the whole country in aggregate, not only an average across treated villages.

In sum, the total impact on child labor will be the net outcome of offsetting income and substitution effects. For instance, the international literature, using different sources of household income variation, has found mixed effects. Some studies find a dominant substitution effect (Duryea & Arends-Kuenning, 2003; Kruger, 2006; and Kruger, 2007). While others suggest a dominant income effect (Dehejia & Gatti, 2005; Dammert, 2008; Del Carpio, 2008; Del Carpio & Marcours, 2009). This paper is the first that uses variation arising from the introduction of ICT to identify the impacts of agricultural profitability on child labor.

The main findings suggest that the intervention generated increases of 16 percent in the value perceived for each kilogram of agricultural production. This led to an increase of 19.7 percent in agricultural profitability (measured by the financial return to agricultural activities). Moreover, this income shock translated into a reduction in the incidence of child (6 – 13 years old) market work equivalent to 14 percentage points and a reduction in child agricultural work of nine percentage points. Overall, the evidence suggests a dominant income effect in the utilization of child labor among isolated rural villages in Peru.

The rest of the paper is organized as follows. Section 2 presents a description of the FITEL program. Section 3 presents an analytical framework to understand the expected outcomes of the intervention. Section 4 presents the dataset used for the empirical analysis. Section 5 describes the empirical approach adopted in the analysis. Section 6 discusses our main results, while Section 7 checks the robustness of these results. Finally, Section 8 concludes.

2. The FITEL Program

In 1992, the Peruvian government privatized all state-owned telecommunications companies and created a Telecommunications Regulatory Authority (OSIPTEL).[2] In May 1993, OSIPTEL created the Fund for Investments in Telecommunications (FITEL) which began to collect a 1% levy charged on gross operating revenues of telecommunications companies in order to fund rural service expansion. In November 2006, FITEL was declared an individual public entity ascribed to the Ministry of Transports and Communications.

The specific FITEL intervention studied here provided at least one public (satellite) payphone to each of the 6,296 targeted villages. To do so, FITEL divided the country into six geographical regions (i.e. north, middle north, middle east, south, middle south, and north

[2] Prior to 1992 the telecommunications sector was state-owned and no private firms existed.

tropical forest). The project was executed by granting a 20-year concession to private operators for public telephone services in each geographical region. The selection of the operator for each region was based on an international auction for the lowest subsidy requested from FITEL for the installation, operation and maintenance of these public services. It is worth noting that all phones, regardless of which operator wins each region, had to be homogeneous with respect to the technology (i.e. satellite vsat phones). Targeted villages were selected by FITEL prior to the auctioning process following the three-phase procedure described below.

2.1 Village Selection Criteria

The selection of the rural villages to benefit from the project was based on the criteria of maximizing the social profitability of the public investment, while minimizing the subsidy. The selection process was composed of three stages. In stage one; FITEL defined the target universe of villages for the intervention. The universe was composed of rural villages with populations between 200 and 3,000 inhabitants that did not have access to ICT. Furthermore, villages in the targeted universe could not be in any future coverage plan of private telecommunications companies. Therefore, targeted villages neither had nor expected to be provided access to ICT.

In stage two; villages in the target universe were grouped in cells with average radius of five kilometers. Cells were formed with the requirement that no village within the cell could either have phone service or be included in the expansion plan of a private operator. Then, one village within each cell (cell center) was pre-selected for treatment (i.e. payphone installation). To be selected as a cell center, the village needed to comply with at least one of the following requirements: have a health center; be accessible (i.e. in connection with rural roads, river crosses or horse paths); have a high school; and have the highest population within the cell or be a central village in the sense that villagers in the cell confluence to that village to market products or get health services. Finally, district capitals without phone services and that were not included in future expansion plans of private operators were automatically selected as cell centers.

Finally, in stage three; field visits were conducted to all of the cell centers. The purpose of this field work was to assess the technical viability of installing payphones. In addition, several workshops were conducted in district capitals that were selected as cell centers. These workshops encouraged the participation of district leaders and representatives of local civil

society. The purpose of these workshops was to assess the convenience of the selected cell centers. After this field work, the list of pre-selected villages was updated and the final list of targeted villages was selected.

The outlined selection criteria suggest that targeted villages in the different geographical regions of the intervention were similar with respect to several development characteristics. Therefore, the empirical strategy will exploit differences in the timing of the intervention across villages in order to identify causal impacts. This timing is briefly explained below.

2.2 Intervention Timing

Once targeted villages were selected, FITEL auctioned 20-year concessions for each one of the six geographical zones: north, middle north, middle east, south, middle south, and north tropical forest. Initially, FITEL planned that all payphones would be operative by the first quarter of year 2002. However, delays in the auctioning process determined that the program rollout lasted until year 2004. This timing is schematized in Figure 1 and spanned from year 2001 through year 2004 covering a total of 6,296 villages.

Provided that the timing of the intervention was not systematically related with the outcomes of interest and/or with variables determining these outcomes; the causal impacts can be identified by exploiting such time variation in phone rollout. Accordingly, the identification strategy will exploit differences in the intervention timing at the village level, which as we will show below was orthogonal to baseline outcomes and to variables plausibly related to them.

3. Expected Outcomes

The mechanisms through which access to ICT may impact agricultural profitability are diverse. First, the presence of ICT greatly decreases the costs associated with searching for information across different markets in order to sell (buy) agricultural production (inputs) in places offering the best prices. Second, by allowing farmers to be informed about the real market price of their crops, ICT increases farmers' bargaining power with traders approaching their villages to buy their production. Third, access to ICT may allow farmers to be informed about weather forecasts and incorporate this knowledge into their planting decisions. This could improve efficiency, for example, less fertilizer may be necessary if better weather information allows farmers to plant at a more optimal time.

The previous mechanisms may coexist, of course, and the aggregate effect reflects all of them. However, a half program survey conducted by FITEL in 2002 among villages that already had a phone reveals that 19.5 percent of treated households use the technology to search for market information. This is the second most important reason for using the phone (the first was social/family communication, at 95.3 percent). Furthermore, when looking only at households engaged in agricultural production, 38 percent report searching market information as the main usage. In addition, 70 percent of households who report using the phone for market information search reveal that the frequency of these searches is either weekly or daily. This evidence suggests that an important mechanism through which the new technologies may have affected agricultural profitability is likely a reduction in search costs. We now present a simple model that formalizes this mechanism.

3.1 Effects on Profitability

We assume that farmers derive utility from their agricultural activity through a Bernoulli utility function defined over output and input prices (net of transport costs) as follows:

$$u\left(P_o, P_i\right) = v\left(P_o\right) - g\left(P_i\right) \tag{1}$$

where P_o denotes output prices, P_i denotes input prices and $v' > 0, v'' \leq 0,$ and $g' > 0$.

In addition, we assume a constant marginal cost *C* of searching for price information in an additional market. Therefore, if a farmer has already searched for prices in N markets, with *O* being the best offered price for his output and *I* the best price found for his input, the expected marginal utility of the N+1 search is given by:

$$B\left(O, I\right) = \left[\int_{o}^{\bar{P}_o} \int_{\underline{P}_i}^{I} \left[v(P_o) - g(P_i)\right] - \left[v(O) - g(I)\right] dG(P_i) dF(P_o)\right] - C \tag{2}$$

where $\bar{P}_o$ and $\underline{P}_i$ represent the maximum possible output price and minimum possible input price respectively. $F(.)$ and $G(.)$ are the CDFs of output and input prices respectively. Notice that (2) assumes that if the utility derived from prices found in the N+1 search is below the reservation utility (derived from prices *O* and *I*), then the farmer will sell his output at price *O* and buy his input at price *I*.[3] So, in that case, the benefit of the N+1 search will be actually a cost of *C*. This depends on the probabilities of getting better price pairs. All else equal, as these probabilities

[3] Notice that this assumes that outputs are sold and inputs purchased in the same market.

fall, will be less attractive to search in another market. Therefore, optimality implies (assuming an interior solution) that the farmer will set his reservation price for output (*R*) and maximum price paid for the input (*M*) by equating the expected marginal benefit of the N+1 search to zero.

Therefore, the reservation price for output and maximum price for the input will be implicitly defined by:

$$B(R,M)=\left[\int_{R}^{\bar{P}_o}\int_{\underline{P}_i}^{M}\left[v(P_o)-g(P_i)\right]-\left[v(R)-g(M)\right]dG(P_i)dF(P_o)\right]-C=0 \qquad (3)$$

The effect of a change in *C* on *R* can be derived from (3) using the implicit function theorem and Leibnitz' rule as follows:

$$\frac{\partial R}{\partial C}=-\frac{\partial B(R,M)/\partial C}{\partial B(R,M)/\partial R}= \qquad (4)$$

$$\frac{1}{-G(M)v'(R)\left[1-F(R)\right]-F'(R)\left[g(M)-E\left(g(P_i)\mid P_i\le M\right)\right]}<0$$

Similarly, the effect of a change in *C* on *M* can be derived from (3) as follows:

$$\frac{\partial M}{\partial C}=-\frac{\partial B(R,M)/\partial C}{\partial B(R,M)/\partial M}= \qquad (5)$$

$$\frac{1}{G'(M)\left[E\left(v(P_o)\mid P_o\ge R\right)-v(R)\right]+\left[1-F(R)\right]g'(M)G(M)}>0$$

Clearly, (4)-(5) imply that reservation prices should rise and maximum prices paid for inputs should fall if search costs decrease. The introduction of ICT dramatically reduced search costs. In particular, the intervention reduced average distance to the nearest communication point from 60 to five kilometers nationwide. Thus, the model implies that average reservation prices will rise (prices paid for inputs will fall) and therefore agricultural profitability will rise following the installation of payphones.

3.2 Effects on Child Labor

In the context of rural villages, child labor in farms is very common. Parents decide how to allocate their children's time between school and work. An increase in agricultural profitability implicitly raises the opportunity cost of schooling. This happens because an additional unit of labor provided to the farm is more valuable when per unit profits are higher. Therefore, the

substitution effect implies that an increased opportunity cost of schooling will generate a reduction in its demand and, consequently, an increase in the utilization of child labor.

On the other hand, an increase in per unit profits raises household income and, assuming that schooling is a normal good while child labor an inferior one, the income effect implies that demand for schooling will increase and utilization of child labor will decrease. As a result, the introduction of ICT generates offsetting substitution and income effects on child labor incidence. The income effect suggests that a reduction in search costs will decrease child labor, while the substitution effect suggests the opposite.

Therefore, the total effect of the introduction of ICT on the utilization of child labor is ex-ante unsigned. The substitution effect implies that child labor will increase with the introduction of ICT, while the income effect implies the opposite. The total effect will therefore depend on the relative weights that parents' utility assigns to consumption versus children's human capital and is, ultimately, an empirical question.

4. The Data

The dataset consists on a unique unbalanced panel of treated villages that has been constructed using several data sources and GIS techniques as follows.

The first data source is the Peruvian Living Standards Measurement Survey (PLSMS) for years 1997 and 2000, succeeded by the Peruvian National Household Survey (ENAHO) for years 2001 through 2007. The ENAHO replaced the PLSMS and most of their questionnaires mimic those of the PLSMS ones. Both surveys are nationally representative. These surveys contain information on demographics, education, income and expenses.

The second source is FITEL's administrative information containing the GPS location of each phone and the date at which the phone became operative. The third source consists of geo-referenced information from the Peruvian Ministry of Transports and Communications regarding the rural network of roads and rivers. Finally, we used NASA information from the Shuttle Radar Topography Mission to construct a gradient map of Peru at a 90 meter cell precision.[4]

We built the final dataset by coding the PLSMS/ENAHO at the village level and inputting the GPS location of each village using information collected during the 2007 Peruvian census. Then, using the geo-coded information on the communications network and land

[4] This dataset is freely available at: http://www2.jpl.nasa.gov/srtm/

gradient, we simulated travel time from each surveyed village to the nearest FITEL phone using the program *SMALLWORD*.[5] Our sample includes only villages situated within a radius of 30 minutes traveling time to the nearest phone (the mean travel time in the final sample is 6 minutes). Our final sample consists of 15,242 household-year and 19,409 children (6 to 13 years old)-year observations, distributed across 2,453 village-year observations. The difference between the intervention timing patterns provided by the sample and the overall program timing is statistically indistinguishable from zero (see Figure 1).[6]

Table one displays descriptive statistics at baseline (pooling 1997 and 2000 data). The average age of household heads is 47, with only 36 percent of them having completed at least secondary education. As expected, the poverty rate in the treated villages is higher than the national average. For instance, 54 percent of households in the treated villages were considered poor, while the national poverty rate was 44 percent for the same period. Agricultural profitability, measured by the ratio of total production value over total costs, reached an average of 9.95. The average farmer reported to sell half of the total agricultural production, consuming 30 percent of it, while using the rest as seeds or for barter. Children sex ratio was about 1, with 51 percent of children being male. Child labor amounts to 43 percent of children reporting market work as their main activity.[7] However, most of them were engaged in agricultural work (35 percent) as their main activity, while only 8 percent reported wage work as the main activity.

5. Empirical Strategy

To estimate the causal impact of ICT on the outcomes of interest, we follow a village-level panel approach which summarizes the overall impact of the program as the difference between mean outcomes before and after the intervention. We estimate regression equations of the following form:

---

[5] Smallworld GIS is one of the leading geographical information systems (GIS) designed for the management of complex utility or telecommunications networks. For details regarding the software and its applications see: http://www.gepower.com/prod_serv/products/gis_software_2010/en/index.htm

[6] As an alternative strategy, we also included observations from villages that were never treated and were situated within an interval of two to four hours away from the nearest phone (pure control villages). After this inclusion, results remain qualitatively unchanged and are available upon request. However, we decided to focus our analyses on treated villages given that all of them shared common baseline characteristics; while pure control villages showed some significant differences at baseline. This might has been expected given that treated villages shared several of the characteristics outlined in the selection criteria explained in Section 2.

[7] Market work includes wage employment, self-employment, agriculture, helping in a family business, and domestic work in an external household.

$$Y_{ijt} = \alpha_j + \phi_t + \beta_1 \cdot Phone_{jt} + X_{ijt}^{'}\gamma + \varepsilon_{ijt} \quad (6)$$

where Y_{ijt} is the outcome of interest for household/child *i*, in village *j* in year *t*. $Phone_{jt}$ is an indicator that takes the value of 1 if village *j* had a phone in year *t*, and 0 otherwise. α_j is a village fixed effect. ϕ_t is a year fixed effect. X_{ijt} is a vector of controls defined in the results tables. Finally, ε_{ijt} is an error term that in all estimations will be clustered at the village level to account for heteroskedasticity and serial correlation in disturbances among dwellers living in the same village.

Some aspects of model (6) merit discussion. First, the village fixed effects control nonparametrically for any time-invariant unobservable characteristics across villages. Second, the year fixed effects control nonparametrically for aggregate yearly shocks across villages in the sample, for example from a particularly dry or rainy year. In this model, estimates of β_1 provide a measure of the program's average effect over the outcomes of interest. Specifically, it provides an estimate of the program's impact in the years after the installation of the phones, relative to the mean in the years prior to installation.

The identification strategy exploits inter-village variation in the timing of the introduction of phones across the sampled villages to identify the effects. The identifying assumption is that, in the absence of the intervention, there would have been no differential changes in the outcomes of interest across the villages over the studied period. To the extent that the timing of the intervention in different villages was chosen in response to actual and forecastable changes in the outcomes of interest, the results would be biased. However, since the date of phones introduction varied substantially across villages, and was chosen far in advance by FITEL officials, this type of endogeneity seems unlikely to have been present.

This key identifying assumption, however, can be partially tested. If treatment timing was indeed orthogonal to potential results, differences in outcomes of interest and other characteristics between villages treated early in the program and those treated later evaluated at pre-treatment periods should not exist. Accordingly, Table two provides evidence showing that baseline differences for households and children treated early (between 2001 and 2002) and late (between 2003 and 2004) are statistically indistinguishable from zero. Moreover, column four of the table displays the F-test p-value for the joint significance of the differences between each of the pairwise comparisons with respect to treatment years evaluated at all pooled pre-treatment

periods. Only one variable out of 17 shows a significant F-test. This result gives us confidence that treatment timing was unrelated to the outcomes of interest and demographic characteristics.

We also estimate a variant of equation (6) in which we add region-specific time trends, as follows:

$$Y_{ijt} = \alpha_j + \phi_t + \beta_1 \cdot Phone_{jt} + X_{ijt}^{'}\gamma + Coast_j \cdot f(t) + Highlands_j \cdot f(t) + Jungle_j \cdot f(t) + \varepsilon_{ijt} \quad (7)$$

This specification controls for quadratic trends in outcomes during the study period, and allows these trends to vary across Peruvian natural regions. The advantage of this specification is that it separates the impact of the arrival of the phones from other ongoing trends in regional outcomes, to the extent that these trends are roughly linear or quadratic.

6. Results and Discussion

6.1 Agricultural Outcomes

We first look at agricultural outcomes. Specifically, we are interested in testing whether access to ICT has led to increases in prices received by farmers for their crops and reductions in prices paid for inputs. However, the survey does not ask directly about prices. Therefore, we look at the real local currency value received per kilogram sold of agricultural production as a proxy for prices received by farmers.[8] The first row of Table three reports estimates of β_1 for proxy prices. Column 1 suggests a 0.16 log-points increase in the value per kilogram sold of agricultural production as a result of the program. This effect is consistent with the theoretical prediction that a decrease in search costs should increase the reservation prices at which farmers sell their produce. Columns 2 and 3 report estimates coming from specifications in which we add controls such as age, sex and education of the household head, household size, and house ownership status. Our estimates remain virtually unchanged and provide further evidence that treatment timing was not correlated with variables that may have affected the outcomes of interest. Finally, column 4 reports estimates from specification (7), which allows for differential trends by region. Again, our results remain qualitatively the same, suggesting that the introduction of ICT has increased the value per kilogram sold by 0.15 log-points (equivalent to 16 percent).

[8] We take this proxy given that we are interested in the amount of income that farmers receive per unit of production. In that way, the survey provides with the detail of the total value obtained for sold production, expressed in local currency, and the total kilograms of production that was sold.

Our second exercise is to test whether ICT has reduced the prices paid for agricultural inputs. Unfortunately, the dataset does not provide information regarding the quantity of inputs used. It only provides information regarding the total annual costs of agricultural activity. However, as the second row of Table three shows, the introduction of ICT has not had any affect on the quantity of agricultural production. Therefore, if we assume that the quantity used of inputs has remained constant as well, the estimated effects on agricultural costs should mainly reflect effects on input prices rather than quantities. Accordingly, column 1 of the third row of Table three shows that ICT has reduced annual agricultural costs by 0.23 log-points. Columns two through four indicate that our estimate is robust to the inclusion of controls and to differential trends by region. The estimated impact in the fully controlled model (column 4) suggests a 0.21 log-point (equivalent to 23.4 percent) drop in agricultural costs.

Furthermore, when we decompose agricultural costs, we observe that direct inputs such as seeds and fertilizer is the subcomponent that has decreased more significantly (0.19 log-points or 21 percent). The quantity needed of these inputs is likely to remain unchanged in order to produce the same quantity of output. Therefore, our findings are suggestive that prices paid for direct inputs have dropped as predicted by the theoretical model. Although estimations on the effects over other cost sub-components are imprecise due to lower sample sizes, they are suggestive in the sense that cost reductions are observed for tradable goods (pesticides and buckets). On the other hand, transportation costs and wages paid have positive signs. This observation is suggestive of an increased participation in markets outside the resident villages and a slightly increased demand for adult labor which will analyze latter when looking at child labor effects.

Regarding overall profitability, the last row of Table three reports impacts for the natural logarithm of the ratio of the value of agricultural production to total costs. This measure of profitability is the continuously compounded annual return to agricultural activities. Our baseline estimate shown in column one evidences that ICT has increased profitability by 0.19 log-points. This estimate is robust to the inclusion of control variables and differential trends by region. The estimate from the fully controlled model (column four) remains qualitatively unchanged suggesting an increase of 0.18 log-points (equivalent to 19.7 percent). It is worth noting that while our estimates may seem large, they are in line with previous literature regarding the effects of ICT. For example, Jensen (2007) reports an increase of nine percent in average profits of

fishermen in Kerala - India as a result of cell phone coverage, while Aker (2010) reports a 29 percent increase in profits of grain traders in Niger after cell phone rollout. Also, Goyal (2010) reports a 33 percent net gain in farmers' profits after the introduction of internet kiosks that provided real time information of soybean market prices. Therefore, our estimates are situated in between previous estimated effects.

Our results show that the intervention significantly increased the profitability of farming activities. Therefore, affected households received an exogenous shock to net income per unit of time devoted to agricultural activities. These results are in line with theoretical expectations and provide an opportunity to test the effects of this shock on households' allocation of their children's time. Accordingly, the next section explores the effect of this intervention on the utilization of child labor.

6.2 Child Labor Effects

As pointed out earlier, we have no a-priori expectations regarding the direction and size of the program's effect on the utilization of child labor. The ultimate effect will depend on whether the income effect dominates the substitution effect. The dataset provides information about the main activity in which each household member was engaged in the week prior to the survey. Therefore, in order to measure child labor utilization, we compute indicators for market work and agricultural work as main activities.[9] Table four reports estimated effects of the intervention on these variables, where the unit of observation is now a child-year.

Our results clearly suggest a negative effect of the program on the utilization of child labor. For instance, column one of row one shows that the introduction of ICT decreased the likelihood of reporting any market work as the main activity by 15 percentage points. This effect is robust to the inclusion of control variables such as sex and age of children, age and education of the household head, and home ownership status (columns two through four). When including differential trends in the specification (column five), the estimated effect remains robust,

[9] These indicators come from answers to a single question in the survey which asks: "During the previous week, what was your main activity either inside or outside the household?". The possible answers were: a) Helped in the household's or relative's business; b) Domestic work in an external household; c) Helped to elaborate products for sale; d) Helped in the agricultural plot or looking after the cattle; e) Sold products: candy, gum, etc.; f) Transported products, bricks, etc.; g) Other type of work; h) Studying. Therefore, the indicator for Market Work takes the value of one if the child chose any option other than Studying and zero otherwise. The indicator for Agricultural Work takes the value of one if the child chose option d) and zero otherwise. It is worth noting that from 2002 onwards, the answers included an additional option as "Domestic work inside the household". I still considered this option as Market Work. However, it was not included in Agricultural Work.

suggesting a reduction of 14 percentage points in the likelihood of reporting any market work as the main activity. When expressed relative to the baseline proportion of children engaged in market work, the estimated effect implies a 32 percent reduction in the probability of reporting market work as the main activity. Therefore, our results suggest a dominant income effect in the utilization of child labor.

We also evaluate effects on agricultural work. Given that we are focused on agricultural households, we would expect that reductions in child labor might be concentrated in agricultural work. Our empirical results confirm such expectations. Column one of row two suggests a 10 percentage point drop in the likelihood of reporting agricultural work as main activity following the intervention. This result is robust to the inclusion of control variables, as shown in columns two through four. In addition, column five reveals that adding differential trends leaves results practically unchanged, suggesting a nine percentage point reduction in the likelihood of agricultural work. When expressed as a percentage reduction with respect to the baseline level of the outcome, our estimates imply a 26.3 percent reduction in the probability of reporting agricultural work as the main activity following the arrival of ICT. Our estimates strongly suggest a dominant income effect in the utilization of child labor among Peruvian rural villages. These findings are consistent with Dammert (2008), who reports a 12.3 percentage point increase in child market work among coca-growing regions after a successful coca eradication program during the late 1990's in rural Peru (which decreased net income of coca farmers).

We further investigate whether the reduced probability of reporting work as the main activity has impacted school enrollment. Row three of Table four reveals that there has been no impact on school enrollment. This result may seem puzzling, but in the context of rural Peru virtually all children are enrolled in some school. For instance, 95 percent of children at baseline reported being enrolled in school. However, given that work and school are mutually exclusive categories in the survey question regarding main activity, our finding of a 14 percentage point reduction in the likelihood of reporting market work as main activity directly translates into an equivalent increase in the likelihood of reporting school as main activity. This implies a 24 percent increase in the probability of reporting school as main activity with respect to the baseline proportion of children that reported school as their main activity. This constitutes a sizeable effect when compared to conditional cash transfer programs that included school attendance as one of the conditions. For instance, Fizsbein and Schady (2009) find that

enrollment increased by 3.3 percentage points in the case of PRAF in Honduras (for children aged six to 13, from a baseline enrollment of 66 percent), 7.5 percentage points for Chile Solidário (for children aged six to 15, from a baseline enrollment of 61 percent), and by 12.8 percentage points for the Red de Proteccion Social in Nicaragua (for children aged seven to 13, from a baseline enrollment of 72 percent).

6.3 Heterogeneous Effects in the Utilization of Child Labor

We next assess heterogeneity in the effects of ICT on child labor with respect to gender and age. Columns two and three of Table five reveal that the probability of reporting any market work as the main activity was reduced evenly (in relative terms) for girls and boys. For instance, boys reduced this probability by 31 percent (0.14/0.46), while girls reduced it by 32 percent (0.13/0.40). This finding suggests no gender specific preferences for child labor reductions as a result of an exogenous income shock. However, when we look into agricultural work, we observe that agricultural work was significantly reduced only for boys. Column five suggests that the probability of reporting agricultural work as main activity fell by 28.7 percent (0.11/0.38) for boys. This pattern is consistent with gender differences in the allocation of time found in previous studies of Peru (Dammert, 2008; Ersado, 2005; Ilahi, 2001; Levison & Moe, 1998; Ray, 2000) where boys are found to be more active in agricultural work.

We further decompose estimated effects by age ranges. Given that the baseline incidence of child labor was different across ages, we should expect that effects might also differ between ages. Accordingly, Panel B of Table five presents differential effects by age and sex. For market work (columns one to three), we observe that for both girls and boys effects are stronger from age 10 onwards. This is consistent with the fact that, at baseline, market work had higher incidence at these age ranges. Similarly, agricultural work (columns four to six) has had stronger impacts for boys at ages above 10 (17 percentage points), and for girls in that same age range (15 percentage points). This is also consistent with the fact that this type of work was more prevalent at these age ranges for boys and girls.

6.4 Adult Labor Effects

So far our findings suggest that agricultural profitability has increased while child labor utilization decreased, with the quantity of agricultural production remaining unchanged. Therefore, if children are somehow productive in the farm, adult labor should have increased to

compensate for the lower child labor utilization. Our dataset provide weekly adult labor supply in hours (for people above 18 years old). Therefore, Table six displays estimates for adult labor supply. While imprecisely estimated, the first row suggests that adult labor supply at the household level has increased by about 4.13 hours a week. Interestingly, when labor supply is decomposed between hours devoted to the family plot and hours worked elsewhere; we find that within plot labor supply has gone up by 4.39 hours a week. By contrast, outside labor supply effects have negative signs of about -0.26 hours a week. These findings are in line with a behavior in which adults compensate for the lower utilization of child labor.

Our data also allow us to assess whether households are more likely to hire external labor. To do so, we compute an indicator which equals unity if the household report any level of wages paid to external workers. The indicator equals zero if the household does not report wages paid to external workers. Estimated impacts are show in row four of Table six. Although imprecisely estimated, the sign of the coefficients is suggestive towards a slight increased utilization of external labor. Such observation is also consistent with a compensation mechanism for the lower utilization of child labor.

7. Robustness Analysis

7.1 Timing of the Effects

Next we assess the timing of the estimated effects to verify their causal interpretation. We estimate an augmented version of model (7) which incorporates a one year lead and a one year lag of the treatment indicator $Phone_{jt}$. The lead indicator represents anticipatory effects. Therefore, if our estimates reflect causal impacts of the program, we expect insignificant estimates for anticipatory effects. The lagged indicator represents post-treatment effects. In that sense, significant estimates would imply that the program had an increasing impact one year after treatment. However, an insignificant effect would imply that program impacts were mainly reflected during the first year of treatment with no significant differential effects thereafter.

Panel A of Table seven shows the estimation results. As expected, none of the coefficients representing anticipatory effects are statistically significant at any conventional level. These results give further confidence regarding the causal interpretation of our estimates. In addition, post-treatment effects are also weak. This means that the main impacts of the

program have been realized during the first year and have neither been notoriously strengthened or reversed thereafter.

7.2 Spillover Effects

As detailed earlier, we are estimating the effects of the program using villages within a range of 30 minutes travel time to the nearest phone. However, the survey provides information coming from villages that are situated farther away. Therefore, we could use these observations to check for possible spillover effects. To do so, we consider observations coming from villages situated within a 2 hour travel time range to the nearest phone. Then we estimate model (7) allowing for differential impacts among villages situated within 30 minutes travel time intervals.

Panel B of Table seven shows estimated program effects. Estimates suggest the inexistence of spillover effects. We observe that all effects are insignificant for villages situated in distances over 30 minutes travel time. This evidences that farmers not living in treated villages don't appear to have travelled to the nearest phone and effectively benefited from it. Therefore, this provides support to believe that the Standard Unit Treatment Value Assumption (SUTVA) holds.

8. Summary and Conclusions

This paper examines the impact of provision of public payphones among isolated villages in rural Peru to identify the effects of information and communication technologies (ICT) on agricultural profitability and child labor. The main results suggest that the value received per kilogram of agricultural production increased by 16 percent following the installation of the phones, while agricultural costs were reduced by 23.4 percent (mainly explained by reductions in costs of direct inputs such as seeds and fertilizer by 21 percent). These impacts together imply an increase of 19.7 percent in agricultural profitability. Moreover, this income shock was translated into a reduction of child market work equivalent to 32 percent of baseline labor supply and a reduction in child agricultural work of 26.3 percent, suggesting a dominant income effect in the utilization of child labor.

A variety of corroborating evidence supports these findings. Results are robust to the inclusion of household characteristics, child characteristics, village fixed effects and differential trends by geographical regions. Positive adult labor supply effects were consistent with a

substitution of lower child labor utilization. There are differential child labor effects by gender and age, suggesting that labor is reduced more for groups with higher ex-ante incidence of it. I find no impact on the extensive margin of school enrollment, which is not surprising given the high school enrollment rates in rural Peru. Finally, the timing of the effects show that no anticipatory effects were present with respect to the outcomes of interest and that the estimated impacts became significant as a result of phones introduction with almost all of the impacts realized during the first year of treatment.

Overall, these results provide evidence of the potential benefits that ICT can offer to poor rural households. By reducing asymmetric information, farmers are able to obtain better prices for their production and inputs following the advent of ICT, thereby increasing their profitability. Moreover, the finding of a dominant income effect in the utilization of child labor suggests that offering cash transfers or subsidies conditional on school attendance may not be necessary for this population. Higher schooling investments after a favorable income shock appear to be incentive compatible among Peruvian rural farmers.

References

Aker, J. (2010). Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *American Economic Journal: Applied Economics, 2*, (3), 46–59.

Brown, J. R., & Goolsbee, A. (2002). Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry. *Journal of Political Economy, 110*, (3), 481–507.

Dammert, A. (2008). Child labor and schooling response to changes in coca production in rural Peru. *Journal of Development Economics, 86*, (1), 164–180.

Dehejia, R., & Gatti, R. (2005). Child Labor: The Role of Income Variability and Access to Credit in a Cross Section of Countries. *Economic Development and Cultural Change, 53*, (4), 913-932.

Del Carpio, J. (2008). Does Child Labor Always Decrease with Income? An Evaluation in the Context of a Development Program in Nicaragua. *World Bank Policy Research Working Paper No. 4694*

Del Carpio, J. & Macours, K. (2009). Leveling the Intra-Household Playing Field: Compensation and Specialization in Child Labor Allocation. *World Bank Policy Research Working Paper No. 4822*

Duryea, S., & Arends-Kuenning, M. (2003). School Attendance, Child Labor, and Local Labor Markets in Urban Brazil. *World Development, 31*, (7), 1165–1178.

Ersado, L. (2005). Child labor and schooling decisions in urban and rural areas: comparative evidence from Nepal, Peru and Zimbabwe. *World Development, 33*, (3), 455–480.

Fiszbein, A. & N. Schady. (2009). Conditional Cash Transfers: Reducing Present and Future Poverty. *World Bank Policy Research Report*.

Goyal. A. (2010). Information, Direct Access to Farmers, and Rural Market Performance in Central India. *American Economic Journal: Applied Economics, 2*, (3), 22–45.

Ilahi, N. (2001). Children's work and schooling: does gender matter? Evidence from the Peru LSMS. *World Bank Policy Research Working Paper No. 2745*.

Jensen, R. (2007). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *Quarterly Journal of Economics*, *122*, (3), 879-924.

Kruger, D. (2006). Child labor and schooling during a coffee sector boom: Nicaragua 1993–1998. In Trabajo Infantil: Teoria y Evidencia desde Latinoamerica. Fondo de Cultura Economica de Mexico, Mexico, D.F.

Kruger, D. (2007). Coffee production effects on child labor and schooling in rural Brazil. *Journal of Development Economics, 82,* (2), 448-463.

Levison, D., & Moe, K. (1998). Household work as a deterrent to schooling: an analysis of adolescent girls in Peru. *The Journal of Developing Areas*, *32,* (2), 339–356.

Ray, R. (2000). Analysis of child labour in Peru and Pakistan: a comparative study. *Journal of Population Economics*, *13,* (1), 3–19.

Stigler, George J. (1961). The Economics of Information. *Journal of Political Economy, 69*, (3), 213–25.

Figure 1: Intervention Timing

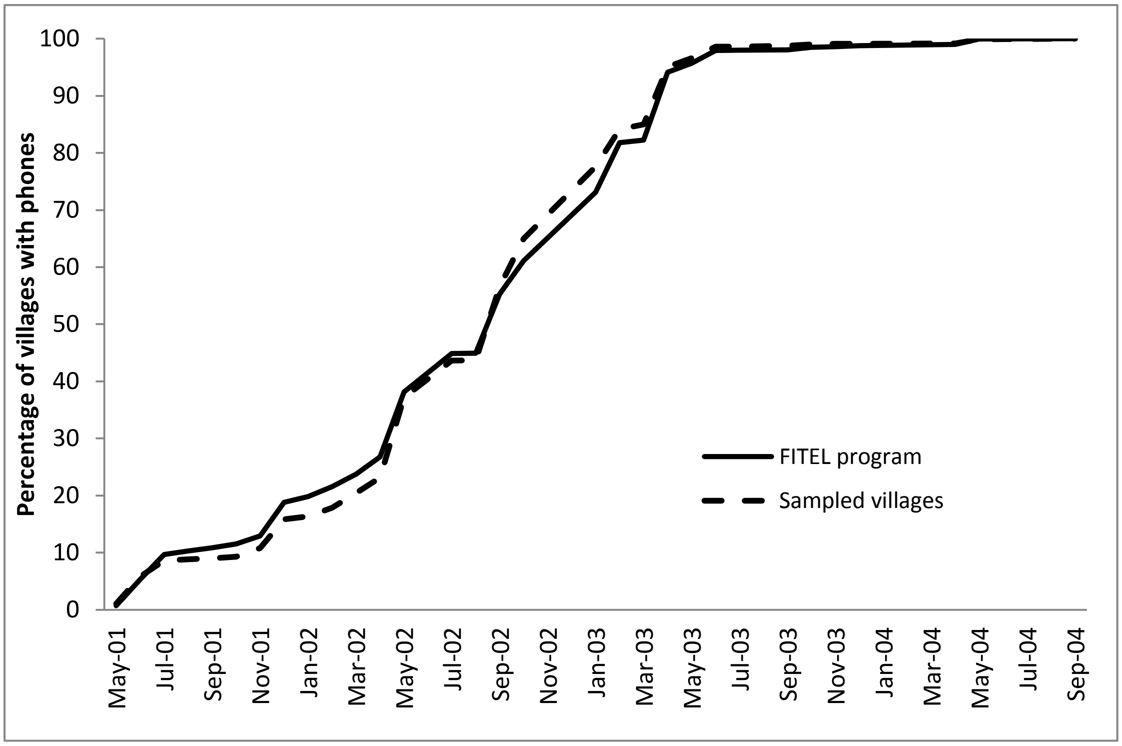

Table 1: Summary statistics at baseline

	N	*Mean*	*S.D.*	*Min*	*Max*
	(1)	(2)	(3)	(4)	(5)
Panel A: Household head characteristics					
Age	585	46.96	14.62	20	94
High education (1=secondary+)	585	0.36	0.48	0	1
Home ownership	585	0.83	0.38	0	1
Poor	585	0.54	0.50	0	1
Migrant	585	0.28	0.45	0	1
Household size	585	5.37	2.07	1	13
Panel B: Agricultural production					
Annual production (kgs.)	585	4,410	6,451	10	35,000
Value per kg. sold (in local currency)	482	1.55	7.03	0.01	131.01
Annual agricultural costs (in local currency)	585	2,196	13,918	1	285,917
Profitability: production (value)/costs	585	9.95	10.38	0.03	49.39
Production sold/total production (kgs.)	585	0.50	0.34	0	1
Production consumed/total production (kgs.)	585	0.30	0.26	0	1
Panel C: Child characteristics					
Age	1138	9.49	2.31	6	13
Gender (1=male)	1138	0.51	0.50	0	1
Market work	1138	0.43	0.49	0	1
Agricultural work	1138	0.35	0.48	0	1
Wage work	1138	0.08	0.26	0	1
School - enrollment	1138	0.95	0.21	0	1
School - main activity	1138	0.57	0.49	0	1

Table 2: Baseline differences

Survey year:	1997	2000	2001	F-test
	Late - Early	Late - Early	Late - T2002	Pairwise
	(1)	(2)	(3)	(4)
Household head characteristics				
Age	-2.732	0.315	0.028	0.56
	(2.270)	(2.271)	(1.068)	
High education (1=secondary+)	0.044	-0.095	-0.077**	0.03**
	(0.065)	(0.065)	(0.031)	
Home ownership	-0.045	-0.055	0.005	0.59
	(0.083)	(0.041)	(0.027)	
Agricultural outcomes (in natural logs)				
Annual production (value)	0.048	-0.005	0.103	0.91
	(0.323)	(0.256)	(0.142)	
Annual production (kgs.)	-0.073	0.096	0.061	0.91
	(0.307)	(0.247)	(0.187)	
Value per kg. sold	0.122	-0.193	0.022	0.38
	(0.245)	(0.133)	(0.107)	
Annual costs	0.068	-0.162	0.013	0.92
	(0.353)	(0.337)	(0.172)	
Profitability: production (value)/costs	-0.020	0.157	0.091	0.81
	(0.267)	(0.265)	(0.130)	
Production sold/total production (kgs.)	-0.082	-0.064	0.087	0.23
	(0.069)	(0.071)	(0.053)	
Production consumed/total production (kgs.)	0.322	0.386*	-0.255	0.16
	(0.203)	(0.212)	(0.203)	
Observations	254	331	1687	2,272
Child characteristics				
Age	0.060	-0.180	-0.033	0.82
	(0.182)	(0.181)	(0.116)	
Gender (1=male)	-0.081	-0.074	-0.029	0.11
	(0.053)	(0.043)	(0.027)	
Child outcomes				
Market work	-0.056	-0.054	-0.045	0.51
	(0.103)	(0.072)	(0.058)	
Agricultural work	-0.045	-0.056	-0.037	0.55
	(0.104)	(0.072)	(0.059)	
Wage work	-0.011	-0.006	-0.008	0.40
	(0.006)	(0.007)	(0.022)	
School - enrollment	0.031	-0.020	-0.043**	0.240
	(0.019)	(0.020)	(0.014)	
School - main activity	0.056	0.054	0.045	0.51
	(0.103)	(0.072)	(0.058)	
Observations	510	628	2314	3,452

Estimated standard errors clustered at the village level in parentheses. Late refers to villages treated during 2003 or 2004. Early refers to villages treated during 2001 or 2002. T2002 refers to villages treated during 2002. Column 4 displays the F-test p-value for joint significance using all pooled pre-treatment year data (1997-2001) regarding pairwise comparisons according to the village specific treatment year.
* Statistically significant at 10% level; ** Statistically significant at 5% level.

Table 3: Agricultural Outcomes

	Estimated Effects				Observations
	(1)	(2)	(3)	(4)	(5)
Dependent variables (in natural logs):					
Value per kg. sold	0.16*	0.16*	0.16*	0.15*	11495
	(0.09)	(0.09)	(0.09)	(0.09)	
Annual production (kgs.)	-0.05	-0.06	-0.06	-0.06	15242
	(0.10)	(0.10)	(0.10)	(0.10)	
Annual costs	-0.23**	-0.24**	-0.24**	-0.21**	15242
	(0.11)	(0.11)	(0.11)	(0.11)	
Direct inputs (seeds and fertilizer)	-0.20*	-0.20**	-0.20*	-0.19*	15242
	(0.10)	(0.10)	(0.10)	(0.10)	
Pesticides	-0.03	-0.05	-0.04	-0.06	6312
	(0.14)	(0.14)	(0.14)	(0.14)	
Buckets for storage	-0.19	-0.21	-0.20	-0.18	5108
	(0.15)	(0.14)	(0.14)	(0.15)	
Tansportation costs	0.16	0.10	0.10	0.04	3435
	(0.28)	(0.27)	(0.27)	(0.25)	
Wages paid	0.05	0.03	0.02	0.03	8950
	(0.13)	(0.13)	(0.13)	(0.12)	
Profitability: production (value)/costs	0.19**	0.18**	0.18**	0.18**	15242
	(0.09)	(0.09)	(0.09)	(0.09)	
Household characteristics	No	Yes	Yes	Yes	
House ownership status	No	No	Yes	Yes	
Differential quadratic trends by natural region	No	No	No	Yes	

Estimated standard errors clustered at the village level in parentheses. All regressions include year and village fixed effects. Household characteristics include household size, as well as sex, age and education level of the household head. Ownership status is an indicator for house formal property. The natural regions are coast, highlands and jungle. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Table 4: Child labor effects

	Estimated Effects					Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:						
Market work	-0.15***	-0.14***	-0.14***	-0.14***	-0.14***	19409
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
Agricultural work	-0.10**	-0.10**	-0.10**	-0.09**	-0.09**	19409
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	
School - enrollment	0.005	0.004	0.004	0.004	0.003	19262
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	
Child characteristics	No	Yes	Yes	Yes	Yes	
Household head characteristics	No	No	Yes	Yes	Yes	
House ownership status	No	No	No	Yes	Yes	
Differential quadratic trends by natural region	No	No	No	No	Yes	

Estimated standard errors clustered at the village level in parentheses. All regressions include year and village fixed effects. Market work includes wage employment, self-employment, agriculture, helping in a family business, domestic work in an external household, among others. Child characteristics include sex and age. Household head characteristics include age and education level. Ownership status is an indicator for house formal property. The natural regions are coast, highlands and jungle. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Table 5: Child labor by gender and age

Dependent Variable:	Market work			Agricultural work		
	All	Boys	Girls	All	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Children (6 - 13 years old)						
Phone	-0.14***	-0.14***	-0.13***	-0.09**	-0.11**	-0.07
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Observations	19391	9721	9670	19391	9721	9670
R-squared	0.40	0.46	0.44	0.41	0.46	0.44
Dependent variable mean at baseline	0.43	0.46	0.40	0.35	0.38	0.33
Panel B: Effects by age						
Phone (age = 6 - 9)	-0.11***	-0.12**	-0.09	-0.07	-0.08	-0.04
	(0.04)	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)
Phone (age = 10 - 13)	-0.18***	-0.19***	-0.18***	-0.14**	-0.17**	-0.15**
	(0.05)	(0.07)	(0.06)	(0.05)	(0.07)	(0.06)

Estimated standard errors clustered at the village level in parentheses. All regressions include year and village fixed effects, child characteristics (sex and age), household head characteristics (age and education level), ownership status (indicator for house formal property), and differential quadratic trends by natural regions (coast, highlands and jungle). * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Table 6: Adult labor effects

	Estimated Effects				Observations
	(1)	(2)	(3)	(4)	(5)
Dependent variables:					
Total weekly labor supply (in hours)	4.21	4.11	4.20	4.13	15242
	(3.00)	(2.99)	(2.97)	(2.98)	
Hours in family plot	4.54	4.38	4.48	4.39	15242
	(2.95)	(2.90)	(2.88)	(2.89)	
Hours outside family plot	-0.33	-0.28	-0.28	-0.26	15242
	(1.16)	(1.15)	(1.15)	(1.14)	
Hired an external worker	0.01	0.02	0.02	0.03	15242
	(0.05)	(0.05)	(0.05)	(0.05)	
Household characteristics	No	Yes	Yes	Yes	
House ownership status	No	No	Yes	Yes	
Differential quadratic trends by natural region	No	No	No	Yes	

Estimated standard errors clustered at the village level in parentheses. All regressions include year and village fixed effects. Household characteristics include household size, as well as sex, age and education level of the household head. Ownership status is an indicator for house formal property. The natural regions are coast, highlands and jungle. * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Table 7: Robustness analysis

Dependent Variable:	Value per kg. sold	Agricultural costs	Profitability value/costs	Market work	Agricultural work
	(1)	(2)	(3)	(4)	(5)
Panel A: Timing of effects					
Lead_Phone (1 year anticipatory effect)	-0.003	0.066	0.003	0.030	0.044
	(0.126)	(0.139)	(0.136)	(0.072)	(0.068)
Phone	0.131+	-0.208**	0.176**	-0.139***	-0.094**
	(0.097)	(0.105)	(0.089)	(0.041)	(0.041)
Lag_Phone (1 year post-treatment effect)	-0.092	0.089	-0.077	0.068*	0.051
	(0.104)	(0.091)	(0.069)	(0.036)	(0.035)
Observations	11495	15242	15242	19391	19391
Panel B: Spillover effects					
Phone - [0 ; 30] minutes	0.149*	-0.213**	0.178**	-0.137***	-0.092**
	(0.087)	(0.105)	(0.089)	(0.041)	(0.041)
Phone - (30 ; 60] minutes	-0.120	0.200	0.205	0.107	0.116
	(0.199)	(0.168)	(0.143)	(0.115)	(0.115)
Phone - (60 ; 90] minutes	-0.313	0.182	0.179	-0.044	-0.038
	(0.197)	(0.213)	(0.120)	(0.107)	(0.106)
Phone - (90 ; 120] minutes	0.298	-0.269	0.343	-0.079	-0.125
	(0.264)	(0.253)	(0.224)	(0.078)	(0.085)
Observations	18329	24304	24304	29992	29992

Estimated standard errors clustered at the village level in parentheses. Regressions in columns (1) to (3) have dependent variables expressed in natural logs and include year and village fixed effects, household head characteristics (age and education level), ownership status (indicator for house formal property), and differential quadratic trends by natural regions (coast, highlands and jungle). Regressions in columns (4) and (5) include all previous controls plus child characteristics (sex and age). +denotes significance at the 18% level; * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.