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

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ABSTRACT

We estimate the impact of access to information and communication technologies on agricultural profitability and child labor among isolated villages in rural Peru. We exploit an intervention that provided at least one public (satellite) payphone to 6,509 rural villages that did not previously have any kind of communication services (either landlines or cell phones). We show that the timing of the intervention was uncorrelated with baseline outcomes and exploit it using a panel dataset of treated villages. Consistent with theoretical expectations, we find that profitability increased by 19.5 percent. Moreover, this income shock translated into a reduction in the likelihood of child market work of 13.7 percentage points and a reduction in child agricultural work of 9.2 percentage points. Overall, the evidence suggests a dominant income effect in the utilization of child labor.

INTRODUCTION

Economic theory emphasizes the importance of information for the efficiency of markets (Stigler, 1961; Brown and Goolsbee, 2002). Accordingly, reductions in information search costs are expected to enhance market effectiveness. Advances in information and communication technologies (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 phones as exogenous shocks. For example, 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. The mechanism behind such results is that fishermen started using the cell phones to gather information regarding markets with better prices (in short supply) while in the sea. Therefore, they started to go directly towards these markets to sell their catch and, as a result, prices were equated across markets and market clearing resulted in eliminating the waste coming from unsold fish that was common before cell phone availability.

In the same vein, Aker (2010) analyses 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.

Recently, Goyal (2010) provides 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, mostly between years 2001 and 2004, to each of the 6,509 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 60km. to 5km. 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 changes in potential 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 circumvent concerns common to previous studies regarding endogenous placement of ICT with respect to the outcomes of interest.

Previous studies regarding the economic effects of ICT concentrate on market outcomes, with a specific focus on price dispersion and market performance. However, none directly address effects of new ICT on producers' profitability and how this potentially increased profitability may affect intra-household decisions regarding the utilization of child labor which is very common in rural Peru. This paper, therefore, contributes with new evidence regarding the effects of ICT not only on market outcomes such as agricultural profitability but also on intra-household decisions. If ICT affects agricultural profitability, expected effects on child labor utilization are unsigned. 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).

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 and Arends-Kuenning, 2003; Kruger, 2006; and Kruger, 2007). While others suggest a dominant income effect (Beegle, Dehejia and Gatti, 2006; Dehejia and Gatti, 2005; Dammert, 2008; Del Carpio, 2008; Del Carpio and 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, and a 23.7 percent reduction in agricultural costs. This led to an increase of 19.5 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 13.7 percentage points and a reduction in child agricultural work of 9.2 percentage points. Overall, the evidence suggests a dominant income effect in the utilization of child labor.

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.

THE FITEL PROGRAM

In 1992, the Peruvian government privatized all state-owned telecommunications companies and created a Telecommunications Regulatory Authority (OSIPTEL). 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 6,509 targeted villages. To do so, FITEL divided the country into seven geographical regions (i.e. north border, north, middle north, middle east, south, middle south, and north 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.

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 phases, as follows:

Phase I: In this phase, 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.

Phase II: Villages in the target universe were grouped in cells with average radius of 5km. 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: (i) have a health center; (ii) be accessible (i.e. in connection with rural roads, river crosses or horse paths); (iii) have a high school; and (iv) 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.

Phase III: This phase consisted of field visits 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.

Intervention timing

Once targeted villages were selected, FITEL auctioned 20-year concessions for each one of the seven geographical zones: north border, 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 2002. However, delays in the auctioning process determined that the program rollout lasted until year 2004. This timing is detailed in Table 1 and spanned from 1999 through 2004. 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.

Table 1: Timing of FITEL intervention

Year of Treatment	Number of Treated Villages	Percent	Cummulative
1999	213	3.27	3.27
2001	1,184	18.19	21.46
2002	2,666	40.96	62.42
2003	2,368	36.38	98.80
2004	78	1.20	100.00
Total	6,509		

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. In the empirical analysis, however, we exclude villages treated in 1999 (north border project). These because the 213 villages treated in 1999 were treated first for potentially endogenous reasons, due to their importance as a border with Ecuador.

EXPECTED OUTCOMES

The mechanisms through which access to ICT may impact agricultural profitability are diverse. First, the presence of ICT can greatly decrease 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 may increase 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 the main mechanism through which the new technologies affected agricultural profitability is likely a reduction in search costs. We now present a simple model that formalizes this mechanism.

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:

$$u\left(P_o, P_i\right) = v\left(P_o\right) - g\left(P_i\right) \quad (1)$$

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:

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

where $\overline{P}_o$ 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.1 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 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:

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

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

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

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

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

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

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

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 km. to 5 km. 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.

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 (decrease) in the prices that farmers get for their outputs (pay for their inputs) 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

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

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 and leisure are normal goods while child labor an inferior one, the income effect implies that demand for schooling and leisure 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 ambiguous.

To formalize the argument, consider a household where the father decides how much time a child will dedicate to school, S, and to work in the farm, F. 2 There is an increasing and concave human capital production function which depends on S, HK(S). Parents derive utility from current consumption, C_c, and human capital of the child. Therefore, parents' utility is given by:

$$U[C_c, HK(S)] \quad (6)$$

where $U' > 0$ and $U'' < 0$ for both arguments. The child's time, T, is assumed to be allocated between S and F:3

$$T = S + F \quad (7)$$

Parents supply L hours of labor inelastically at an hourly profit of Wp; their contribution to consumption is thus Y=L*Wp. In addition, each unit of child labor is assumed to contribute a per unit profit of $P_c(C, P_o, P_i) = R(C, P_o, P_i) - M(C, P_o, P_i)$ towards household consumption.

Therefore, the household budget constraint is given by:

$$C_c \leq Y + F \cdot P_c(C, P_o, P_i) \quad (8)$$

In that way, the household problem is to maximize (6) with respect to C_c and S subject to (7) and (8). This maximization yields a Marshallian demand for F of the form:

[2] I assume that working in the farm is not an activity that provides human capital to the child.
[3] For ease of exposition we do not introduce leisure explicitly as a choice variable. However, under the assumption that both schooling and leisure are normal goods, implications for optimal time allocation towards child labor are unaltered.

$$F(P_c(C,P_o,P_i),Y,T) \quad (9)$$

Alternatively, minimization of expenditures holding utility at a constant level, $\bar{U}$, yields a compensated demand for F of the form:

$$\tilde{F}(P_c(C,P_o,P_i),\bar{U},T) \quad (10)$$

Therefore, the Slutsky equation implies the following:

$$\frac{\partial \tilde{F}(P_c,\bar{U},T)}{\partial C} = \frac{\partial F(P_c,Y,T)}{\partial P_c}\frac{\partial P_c}{\partial C} - \frac{\partial F(P_c,Y,T)}{\partial Y}\tilde{F}(P_c,\bar{U},T)\frac{\partial P_c}{\partial C} \quad (11)$$

Rearranging (11) provides us with the Substitution and Income effect decomposition:

$$\underbrace{\frac{\partial F(P_c,Y,T)}{\partial C}}_{TotalEffect} = \underbrace{\frac{\partial \tilde{F}(P_c,\bar{U},T)}{\partial C}}_{SubstitutionEffect<0} + \underbrace{\underbrace{\frac{\partial F(P_c,Y,T)}{\partial Y}}_{<0}\underbrace{\tilde{F}(P_c,\bar{U},T)}_{\geq 0}\underbrace{\frac{\partial P_c}{\partial C}}_{<0}}_{IncomeEffect\geq 0} \quad (12)$$

Clearly, the effect of a decrease in search costs due to the introduction of ICT is 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.

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 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. Tables 2, 3 and 4 show the distribution of the sample by survey year and treatment timing. In addition, Figure 1 displays the villages included in the sample colored by year of intervention.6

Table 2: Household sample size by survey year and treatment timing

Survey year	Treated early	Treated late	Total sample
(1)	(2)	(3)	(4)
1997	161	93	254
2000	224	107	331
2001	1,132	767	1,899
2002	1,409	666	2,075
2003	1,127	572	1,699
2004	615	393	1,008
2005	1,604	916	2,520
2006	1,610	862	2,472
2007	2,047	937	2,984
Total	9,929	5,313	15,242

The sample consists of households reporting both agricultural production and costs. Treated early refers to households in villages that received a phone between 2001 and 2002. Treated late refers to households in villages that received a phone between 2003 and 2004.

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

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 2.1.

Table 3: Children sample size by survey year and treatment timing

Survey year	Treated early	Treated late	Total sample
(1)	(2)	(3)	(4)
1997	353	157	510
2000	423	205	628
2001	1,605	1,001	2,606
2002	1,923	903	2,826
2003	1,433	729	2,162
2004	872	469	1,341
2005	2,061	1,161	3,222
2006	1,858	979	2,837
2007	2,122	1,155	3,277
Total	12,650	6,759	19,409

The sample consists of children between 6 and 13 years old. Treated early refers to children in villages that received a phone between 2001 and 2002. Treated late refers to children in villages that received a phone between 2003 and 2004.

Table 4: Village sample size by survey year and treatment timing

Survey year	Treated early	Treated late	Total sample
(1)	(2)	(3)	(4)
1997	30	17	47
2000	40	19	59
2001	149	93	242
2002	232	108	340
2003	187	90	277
2004	102	59	161
2005	264	150	414
2006	264	139	403
2007	343	167	510
Total	1,611	842	2,453

The sample refers to villages receiving a phone. Treated early refers to villages that received a phone between 2001 and 2002. Treated late refers to villages that received a phone between 2003 and 2004.

Figure 1: Sampled villages by treatment timing

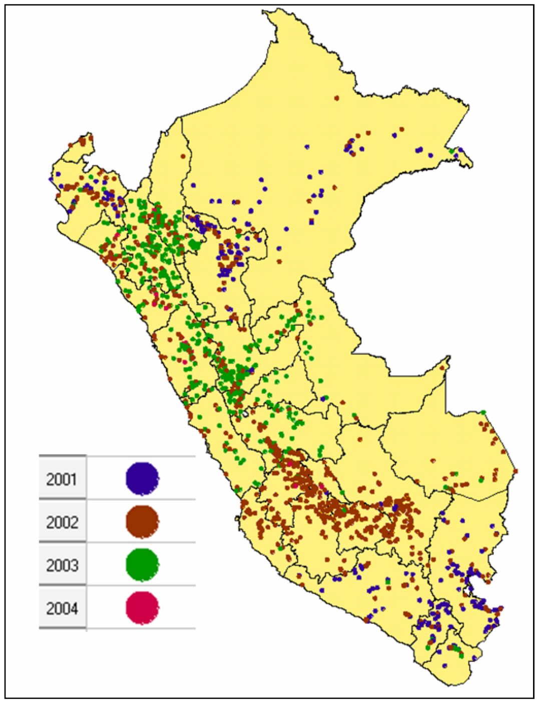


Table 5 displays descriptive statistics at baseline (pooling 1997 and 2000 data). The average age of household heads is 47, with only 36 percent of them having completed at least secondary education. As expected, the poverty rate in the treated villages is higher than the national average. For instance, 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.

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

Table 5: Summary statistics at baseline (1997 – 2000)

	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	4409.72	6451.20	10	35000
Value per kg. sold (in local currency)	482	1.55	7.03	0.01	131.01
Annual costs (in local currency)	585	2195.66	13917.73	1.00	285917.00
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

Child labor showed an upward gradient with respect to age. Figure 2 decomposes baseline levels of reported market work by age and sex. The proportion of children that reported market work as their main activity ranges from 28 percent for age 6, until 55 percent for age 13. The positive gradient is observed for both boys and girls. However, we observe that for the majority of ages, the incidence of child labor is higher for boys. This observation becomes evident when looking at agricultural work in Figure 3. Here we still observe an increasing gradient of child labor for both boys and girls, but with boys being generally more active until age 11 and then girls catching up at ages 12 and 13. Finally, when observing wage work in Figure 4, we no longer distinguish a sustained increasing gradient. By contrast, we observe an inverted U-shape until age 12. In addition, a distinct feature is that girls are generally more active than boys. This might be explained by the fact that one of the main components of wage work is domestic work in an external household, which is a type of work where girls are preferred.

Figure 2: Child market work at baseline (1997 – 2000)

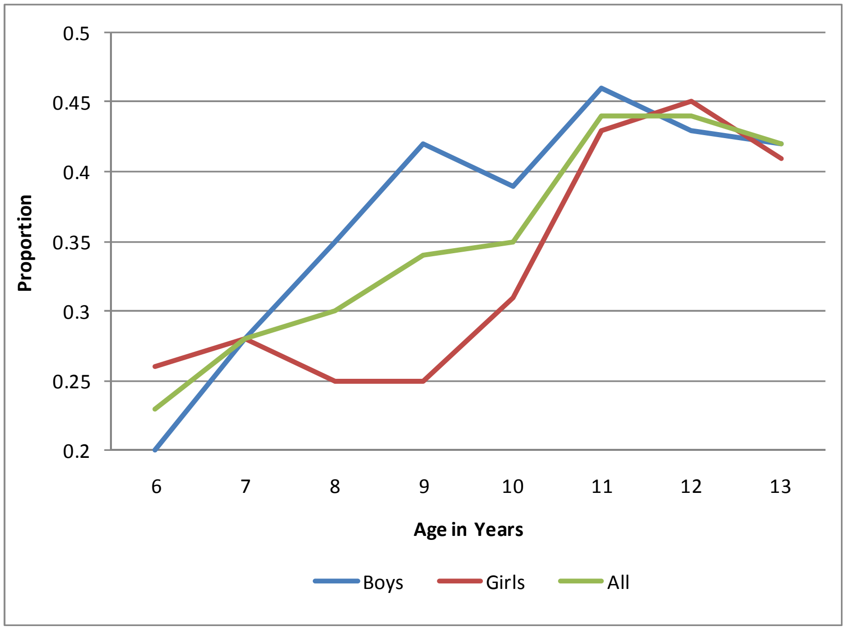


Figure 3: Child agricultural work at baseline (1997 – 2000)

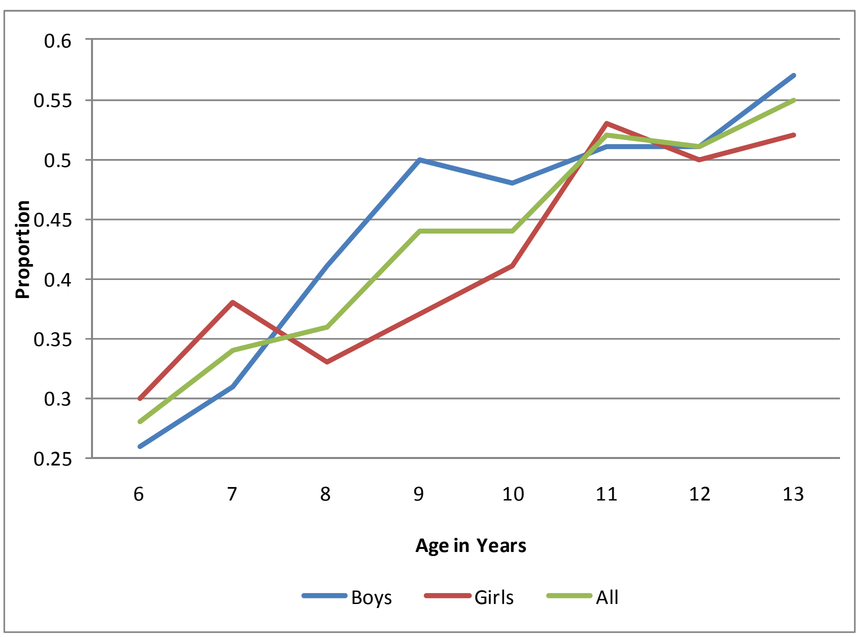
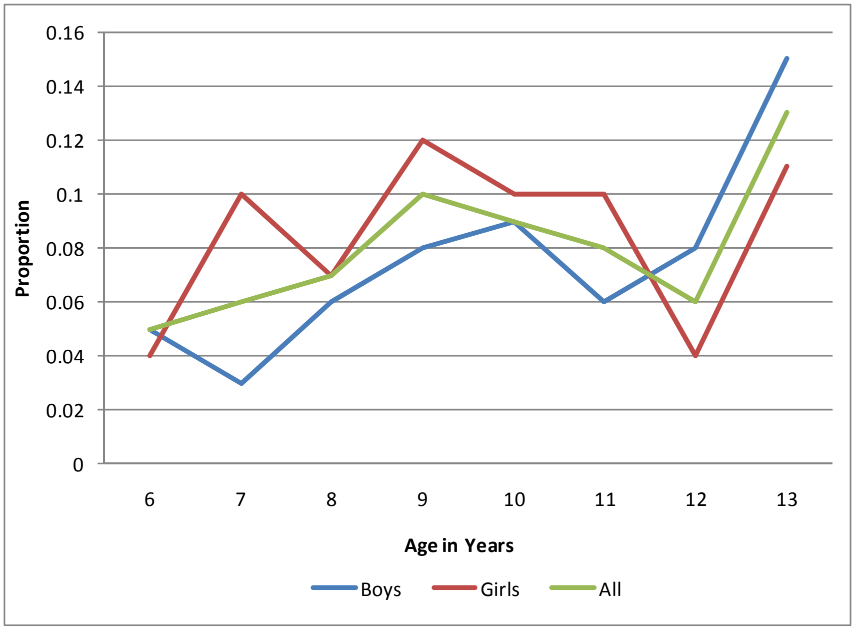


Figure 4: Child wage work at baseline (1997 – 2000)



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:

$$O_{ijt} = \alpha_j + \phi_t + \beta_1 \cdot Post_{jt} + X'_{ijt}\gamma + \varepsilon_{ijt} \quad (13)$$

where Oijt is the outcome of interest for household/child i, in village j in month-year t. $Post_{jt}$ is an indicator that takes the value of 1 if village j had a phone in month-year t, and 0 otherwise. α_j is a village fixed effect. ϕ_t is a month-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 (13) merit discussion. First, the village fixed effects control nonparametrically for any time-invariant unobservable characteristics across villages. Second, the month-year fixed effects control nonparametrically for aggregate monthly shocks across villages in the sample, for example from a particularly dry or rainy month. 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.

To interpret these estimates as causal, the key identifying assumption is that, absent the intervention, villages treated in the first stages of the program and those treated later would have shared the same trends with respect to the outcomes of interest. Moreover, 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, Tables 6 and 7 provide evidence showing that baseline differences for households and children treated earlier (between 2001 and 2002) and later (between 2003 and 2004) are statistically indistinguishable from zero. This result gives us confidence that treatment timing was unrelated to the outcomes of interest and demographic characteristics.

Table 6: Baseline differences for agricultural households

Survey year:	1997	2000	2001
	Late - Early	Late - Early	Late - T2002
	(1)	(2)	(3)
Household head characteristics			
Age	-2.732	0.315	0.028
	(2.270)	(2.271)	(1.068)
High education (1=secondary+)	0.044	-0.095	-0.077**
	(0.065)	(0.065)	(0.031)
Home ownership	-0.045	-0.055	0.005
	(0.083)	(0.041)	(0.027)
Agricultural outcomes (in natural logs)			
Annual production (value)	0.048	-0.005	0.103
	(0.323)	(0.256)	(0.142)
Annual production (kgs.)	-0.073	0.096	0.061
	(0.307)	(0.247)	(0.187)
Value per kg. sold	0.122	-0.193	0.022
	(0.245)	(0.133)	(0.107)
Annual costs	0.068	-0.162	0.013
	(0.353)	(0.337)	(0.172)
Profitability: production (value)/costs	-0.020	0.157	0.091
	(0.267)	(0.265)	(0.130)
Production sold/total production (kgs.)	-0.082	-0.064	0.087
	(0.069)	(0.071)	(0.053)
Production consumed/total production (kgs.)	0.322	0.386*	-0.255
	(0.203)	(0.212)	(0.203)
Observations	254	331	1687

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. 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.
* Statistically significant at 10% level; ** Statistically significant at 5% level.

Table 7: Baseline differences for children between 6 and 13 years old

Survey year:	1997	2000	2001
	Late - Early	Late - Early	Late - T2002
	(1)	(2)	(3)
Child characteristics			
Age	0.060	-0.180	-0.033
	(0.182)	(0.181)	(0.116)
Gender (1=male)	-0.081	-0.074	-0.029
	(0.053)	(0.043)	(0.027)
Child outcomes			
Market work	-0.056	-0.054	-0.045
	(0.103)	(0.072)	(0.058)
Agricultural work	-0.045	-0.056	-0.037
	(0.104)	(0.072)	(0.059)
Wage work	-0.011	-0.006	-0.008
	(0.006)	(0.007)	(0.022)
School - enrollment	0.031	-0.020	-0.043*
	(0.019)	(0.020)	(0.014)
School - main activity	0.056	0.054	0.045
	(0.103)	(0.072)	(0.058)
Observations	510	628	2314

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. 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.
* Statistically significant at 5% level.

We also estimate a variant of equation (13) in which we add region-specific time trends, as follows:

$$O_{ijt} = \alpha_j + \phi_t + \beta_1 \cdot Post_{jt} + X'_{ijt}\gamma + Coast_j \cdot f(t) + Highlands_j \cdot f(t) + Jungle_j \cdot f(t) + \varepsilon_{ijt} \quad (14)$$

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.

RESULTS AND DISCUSSION

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 8 reports estimates of β_1 for proxy prices. Column 1 suggests a 0.157 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 (14), 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 0.149 log-points (equivalent to 16 percent).

Table 8: Estimated effects on agricultural outcomes

	Estimated Effects				Observations
	(1)	(2)	(3)	(4)	(5)
Dependent variables (in natural logs):					
Value per kg. sold	0.157*	0.155*	0.158*	0.149*	11495
	(0.086)	(0.085)	(0.086)	(0.087)	
Annual production (kgs.)	-0.051	-0.060	-0.058	-0.063	15242
	(0.098)	(0.098)	(0.097)	(0.097)	
Annual costs	-0.232**	-0.236**	-0.235**	-0.213**	15242
	(0.108)	(0.107)	(0.107)	(0.105)	
Profitability: production (value)/costs	0.190**	0.184**	0.182**	0.178**	15242
	(0.089)	(0.089)	(0.089)	(0.089)	
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. Weighted regressions using the inverse of sampling probability to reflect survey design. All regressions include month-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.

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 8 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, the estimated effects on agricultural costs should mainly reflect effects on input prices rather

[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.

than quantities. Accordingly, column 1 of the third row of Table 8 shows that ICT has reduced annual agricultural costs by 0.232 log-points. Columns 2 through 4 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 0.213 log-point (equivalent to 23.7 percent) drop in agricultural costs. The estimated impacts are in line with the theoretical predictions, in the sense that the reduction in search costs should decrease prices paid for inputs.

Given that farmers are receiving better prices for their output and paying lower prices for their inputs, profitability of farming activity has increased. The fourth row of Table 8 reports estimates of β_1 for the natural logarithm of the ratio of the value of agricultural production to total costs as our measure of profitability.[9] Our baseline estimate shown in column 1 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 4) remains qualitatively unchanged suggesting an increase of 0.178 log-points (equivalent to 19.5 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 9 percent in average profits of fishermen in Kerala - India as a result of cellphone coverage, while Aker (2010) reports a 29 percent increase in profits of grain traders in Niger after cellphone 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 clearly 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 our theoretical predictions 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.

Child labor effects

As pointed out in the theoretical section, we have no a-priori expectation 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.

[9] This measure is the continuously compounded annual return to agricultural activities.

Therefore, in order to measure child labor utilization, we compute indicators for market work, agricultural work, and wage work as main activities.[10] Table 9 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 1 of row 1 shows that the introduction of ICT decreased the likelihood of reporting any market work as the main activity by 14.6 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 2 through 4). When including differential trends in the specification (column 5), the estimated effect remains robust, suggesting a reduction of 13.7 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 31.9 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.

[10] 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, eICT.; f) Transported products, bricks, eICT.; 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. The indicator for Wage Work takes the value of one if the child chose any other option other that Studying or Agricultural Work, while 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 included neither in Wage nor in Agricultural Work.

Table 9: Estimated effects on children's outcomes

	Estimated Effects					Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:						
Market work	-0.146***	-0.142***	-0.140***	-0.140***	-0.137***	19409
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	
Agricultural work	-0.098**	-0.096**	-0.095**	-0.094**	-0.092**	19409
	(0.041)	(0.040)	(0.040)	(0.040)	(0.041)	
Wage work	-0.024*	-0.022*	-0.022*	-0.022*	-0.021*	19409
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	
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. Weighted regressions using the inverse of sampling probability to reflect survey design. All regressions include month-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.

We also evaluate separate effects on agricultural and wage 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 1 of row 2 suggests a 9.8 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 2 through 4. In addition, column 5 reveals that adding differential trends leaves results practically unchanged, suggesting a 9.2 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.

Wage work has also been affected by the program, with a smaller absolute effect. Our preferred estimate (Table 9 – column 5) suggests a 2.1 percentage point reduction. However, when expressed relative to the baseline level, the estimate implies a 26.3 percent reduction in the probability of reporting wage work as the main activity. All of 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 4 of Table 9 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 13.7 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 6 to 13, from a baseline enrollment of 66 percent), 7.5 percentage points for Chile Solidário (for children aged 6 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 7 to 13, from a baseline enrollment of 72 percent).

Heterogeneous effects in utilization of child labor

We next assess heterogeneity in the effects of ICT on child labor with respect to gender and age. Columns 2 and 3 of Table 10 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% (0.143/0.46), while girls reduced it by 32% (0.128/0.40). This finding suggests no gender specific preferences for child labor reductions as a result of an exogenous income shock. However, when market work is disaggregated into agricultural and wage work, we observe that agricultural work was significantly reduced only for boys while wage work was impacted only for girls. Column 5 suggests that the probability of reporting agricultural work as main activity fell by 28.7% (0.109/0.38) for boys. Column 9 shows that the probability of reporting wage work as main activity fell by 51.5% (0.036/0.07) for girls.

Therefore, it is clear that the overall impact of ICT on the probability of performing some kind of market work was mainly concentrated on agricultural work for boys and wage work for girls. 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 and Moe, 1998; Ray, 2000). Boys are generally more active in agricultural work while girls are more active in wage work (mainly composed by domestic work). This pattern was also confirmed by our baseline data (Figure 4) where it was shown that girls were more active than boys for most of the age range.

Table 10: Child labor by gender and age

Dependent Variable:	Market work			Agricultural work			Wage work		
	All	Boys	Girls	All	Boys	Girls	All	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All Children (6 - 13 years old)									
Post	-0.137***	-0.143***	-0.128***	-0.092**	-0.109**	-0.074	-0.021*	-0.001	-0.036**
	(0.041)	(0.048)	(0.048)	(0.041)	(0.048)	(0.046)	(0.012)	(0.013)	(0.018)
Observations	19391	9721	9670	19391	9721	9670	19391	9721	9670
R-squared	0.40	0.46	0.44	0.41	0.46	0.44	0.17	0.25	0.26
Dependent variable mean at baseline	0.43	0.46	0.40	0.35	0.38	0.33	0.08	0.08	0.07
Panel B: Effects by age									
Post (age = 6 - 9)	-0.113***	-0.117**	-0.090	-0.065	-0.076	-0.038	-0.017	0.004	-0.032
	(0.043)	(0.052)	(0.060)	(0.040)	(0.050)	(0.052)	(0.015)	(0.016)	(0.022)
Post (age = 10 - 13)	-0.176***	-0.193***	-0.183***	-0.136**	-0.166**	-0.145**	-0.022	-0.003	-0.032
	(0.052)	(0.072)	(0.064)	(0.053)	(0.071)	(0.063)	(0.015)	(0.020)	(0.024)

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. All regressions include month-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.

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 10 presents differential effects by age and sex. For market work (columns 1 to 3), 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 (Figure 2). Similarly, agricultural work (columns 4 to 6) has had stronger impacts for boys at ages above 10 (16.6 percentage points), and for girls in that same age range (14.5 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 (Figure 3). Finally, wage work effects vanish when different age ranges are taken into account.

Table 11 – Panel A tests for heterogeneous effects of ICT on child labor with respect to parental education. Columns 1 and 2 reveal that reductions in the probability of reporting any kind of market work as the main activity were proportionately greater for children in households where the head has achieved at least a high school degree. For instance, in households where the head did not finish high school, the reduction in market child labor was equivalent to 28% (0.129/0.46). However, in households where the head holds a high school or higher degree, this reduction accounted for 40% (0.143/0.36). This evidence shows that parents with relatively higher education take their children out of working activities at a higher rate than their lower educated counterparts. This effect might imply that higher educated parents value human capital accumulation for their children more that their less educated peers. However, it could also be that the introduction of ICT has had stronger income impacts among households with relatively more educated heads. Indeed, panel B suggests that households with higher educated parents experienced higher reduction in

agricultural costs when compared to their lower educated counterparts (0.375 versus 0.213 log-points).

Table 11: Estimated effects by parental education

Panel A: Child outcomes						
Dependent Variable:	Market work		Agricultural work		Wage work	
	Low educ.	High educ.	Low educ.	High educ.	Low educ.	High educ.
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.129***	-0.143**	-0.105**	-0.035	-0.003	-0.057*
	(0.047)	(0.062)	(0.046)	(0.064)	(0.013)	(0.031)
Observations	13196	6195	13196	6195	13196	6195
R-squared	0.43	0.52	0.44	0.52	0.23	0.30
Baseline mean	0.46	0.36	0.40	0.24	0.06	0.11
Panel B: Agricultural outcomes						
Dependent Variable (in natural logs):	Value per kg. sold		Agricultural costs		Profitability value/costs	
	Low educ.	High educ.	Low educ.	High educ.	Low educ.	High educ.
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.195*	0.020	-0.213*	-0.375**	0.196**	0.131
	(0.100)	(0.140)	(0.115)	(0.184)	(0.094)	(0.165)
Observations	8451	3044	11217	4025	11217	4025
R-squared	0.41	0.46	0.46	0.58	0.43	0.47

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. Low education refers to household head with primary or lower education. High education refers to household head with secondary or higher education. All regressions in Panel A include month-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). Regressions in Panel B include all previous controls with the exception of child characteristics (sex and age). * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

However, when we consider agricultural and wage work separately, (panel A - columns 3 to 6) we find that agricultural work was significantly reduced only among children in households with less educated heads, while wage work was reduced only for children with more educated parents. The probability of reporting agricultural work as main activity fell by 26.3% (0.105/0.40) for children with less educated parents, while the probability of reporting wage work as main activity fell by 51.8% (0.057/0.11) for children with more educated parents.

These findings reflect the fact that agricultural work was much more common at baseline among children with less educated parents. At baseline, 43.5% of children with less educated parents reported agricultural work as their main activity, while only 30.6% of children with more educated parents did so. In addition, as columns 5 and 6 of panel B show, agricultural profitability has enjoyed a higher impact among households with less educated heads (0.196 log-points). Therefore, the 10.5 percentage point reduction in agricultural work among children in households with less educated parents following the introduction of ICT brought the initial proportions nearly into equality.

A similar result holds for wage work. At baseline, 6.2% of children with less educated parents reported wage work as their main activity, while 10.8% of children with more educated parents did so. Therefore, the 5.7 percentage point reduction in wage work among households with more educated parents brought these proportions into near equality.

<u>*Sensitivity analysis*</u>

Column 1 of Table 12 shows estimation results for child labor excluding households living on the coast. Notice that estimated impacts for market and agricultural work are stronger than the estimated effect for the whole country. This is explained by the fact that child labor is much less common on the coast than in the rest of Peru. For instance, at baseline, only 21% of children living on the coast reported having some type of market work as their main activity. By contrast, this figure was 44% in the rest of the country. Similarly, the proportion of children that reported agricultural work to be their main activity at baseline was 19% in the coast and 43% in the rest of the country. Thus, we observe relatively stronger effects of ICT in zones where the ex-ante level of child labor was greater.

Table 12: Child labor sensitivity analysis

	Excluding coast	%Poor<median	%Poor>median	Low population density<median	High population density>median	Without migrants
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:						
Market work	-0.153***	-0.133***	-0.135**	-0.043	-0.161***	-0.176***
	(0.046)	(0.051)	(0.065)	(0.054)	(0.062)	(0.052)
Observations	17193	9317	10074	9274	10117	13254
R-squared	0.40	0.40	0.42	0.44	0.40	0.43
Agricultural work	-0.118***	-0.061	-0.120*	-0.003	-0.122**	-0.119**
	(0.046)	(0.049)	(0.063)	(0.051)	(0.062)	(0.053)
Observations	17193	9317	10074	9274	10117	13254
R-squared	0.40	0.41	0.42	0.43	0.40	0.43
Wage work	-0.012	-0.040**	-0.001	-0.029	-0.008	-0.029**
	(0.013)	(0.016)	(0.016)	(0.022)	(0.000)	(0.014)
Observations	17193	9317	10074	9274	10117	13254
R-squared	0.17	0.20	0.17	0.21	0.15	0.19

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. Market work includes wage employment, self-employment, agriculture, helping in a family business, domestic work in an external household, among others. All regressions include month-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). Percentage of poor people and population density refer to the district of residency (data from the 1993 Peruvian Census). * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

When looking at wage work, on the other hand, the exclusion of children living on the coast leads to insignificant effects. This is also explained by the fact that wage work among children is more common on the coast than in the rest of the country. At baseline, 11% of children living on the coast reported wage work as their main activity, while only 7% did so in the rest of the country. Therefore, reductions in wage work have also been concentrated in the zone where this kind of labor was more common.

We now explore whether program effects were similar for poor and better-off areas of the country. To do this, we merge our data with the 1993 census and classify sample villages according to the district in which they are located. After this, we split the sample into villages located within districts above and below the median of the 1993 district-level poverty rate distribution. Columns 2 and 3 display estimation results for both sub-samples. Our results suggest virtually the same effect of ICT on child market work for poor and non-poor villages (13.5 and 13.3 percentage point reductions respectively). However, reductions in the incidence of agricultural work are only significant in the poorest districts, while wage work was significantly reduced only in non-poor districts. These findings are consistent with earlier results in that reductions in different types of child labor are stronger in zones with relatively higher baseline incidence of that type of labor. For instance, at baseline, 47% of children living in the poorest districts reported having agricultural work as their main activity, while only 36% did so in non-poor areas. Similarly, 9% of children living in non-poor areas reported wage work as their main activity at baseline, while only 6.5% did so in poorer districts.

Next we classified our sample villages by population density at the district level using the 1993 census. Columns 4 and 5 show results for the resulting subsamples. Interestingly, we observe that reductions in the probability of children reporting market and agricultural work as main activities are only significant among villages located in districts above the median density. These results are perhaps not surprising given that denser areas have more potential workers to replace the decreased child labor. By contrast, in areas with lower density, the incidence of child labor has remained unchanged given the relatively lower external labor supply that may have served to replace children in the household's labor needs.

Finally, column 6 shows that when we exclude migrants (defined as children living in households where the head was born outside the district of current residency), estimated effects become stronger than those obtained using the whole sample. This finding suggests that migrant households may need more labor in order to establish some economic security in a relatively new place. Therefore, these households may have used relatively higher levels of child labor over time than non-migrant counterparts. For instance, 45% of children living in migrant households reported, at baseline, market work as their main activity, while only 37% of children living non-migrant households did so. Similarly, 37% of children living in migrant households reported agricultural work as their main activity, while only 26% of children living non-migrant households did so.

The relation between profitability and child labor

Under the assumption that the only channel trough which ICT impacted child labor was agricultural profitability, we could use the exogenous intervention studied here to instrument profitability and recover an estimate of the causal effect of profitability on child labor. To do so, we estimate the following system of equations by 2SLS:

$$\mathrm{P}_{hjt} = \alpha_j + \phi_t + \beta_2 \cdot \mathrm{P}ost_{jt} + X'_{hjt}\gamma + Coast_j \cdot f(t) + Highlands_j \cdot f(t) + Jungle_j \cdot f(t) + \varepsilon_{hjt} \quad (15)$$

$$W_{ihjt} = \alpha_j + \phi_t + \beta_1 \cdot \hat{\mathrm{P}}_{hjt} + X'_{ihjt}\gamma + Coast_j \cdot f(t) + Highlands_j \cdot f(t) + Jungle_j \cdot f(t) + \varepsilon_{ihjt} \quad (16)$$

where P_{hjt} denotes agricultural profitability of household h in village j at time t, and W_{ihjt} denotes the child labor indicator for kid i of household h in village j at time t. The rest of variables are defined as in (14).

Equation (15) denotes the first stage regression, while model (16) is the second stage regression where profitability has been instrumented with the indicator for the presence of a phone. We estimate the system using observations of children living in households that reported both agricultural production and costs. Column 1 of Table 13 reports the estimate of β_2, while columns 2 to 4 report estimates of β_1 for the different types of labor.

Table 13: Effects of profitability on child labor

Dependent Variable:	Profitability value/costs	Market work	Agricultural work	Wage work
	(1)	(2)	(3)	(4)
Post	0.206**			
	(0.103)			
Instrumented Productivity: log (value/costs)		-0.749***	-0.544**	-0.093
		(0.238)	(0.232)	(0.057)
Observations	15472	15472	15472	15472
R-squared	0.47	0.42	0.42	0.18

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. Regression in column (1) is the first stage and has the dependent variable expressed in natural logs and include month-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 (2) to (4) are the second stage for child labor where log productivity has been instumented with the presence of a telephone in the village. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Column 2 suggests that an increase of 0.1 log-points in agricultural profitability translates into a decrease of 7.5 percentage points in the likelihood of reporting market work as the main activity. Considering that 0.1 log-points is equivalent to 10.5%, and that 7.5 percentage points represent a decrease of 17.4% with respect to the baseline incidence of market work; the implied elasticity of child market work with respect to agricultural profitability is -1.66. This implies that a 1% increase in agricultural profitability translates into a decrease of 1.66% in the likelihood of a child reporting market work as her main activity.

Following a similar procedure, column 3 implies an elasticity of child agricultural work with respect to agricultural profitability of -1.48. The interpretation is that a 1% increase in agricultural profitability translates into a decrease of 1.48% in the likelihood of a child reporting agricultural work as her main activity. Finally, column 4 suggests that the relation between agricultural profitability and child wage work is weak. This was somehow expected given that reduced form estimates were not very precise and only significant for girls. This evidence confirms that agricultural profitability has affected the types of child labor in which it has generated incentives and trade-offs mechanisms between income and substitution effects.

ROBUSTNESS ANALYSIS

Falsification test

Next we conduct a falsification test in the spirit of Granger (1969) to verify the causal interpretation of our estimates. We estimate an augmented version of model (14) which incorporates a one year lead and a one year lag of the treatment indicator $Post_{jt}$. 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.

Table 14 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.

Table 14: Falsification test

Dependent Variable:	Value per kg. sold	Agricultural costs	Profitability value/costs	Market work	Agricultural work	Wage work
	(1)	(2)	(3)	(4)	(5)	(6)
Lead_Post (1 year anticipatory effect)	-0.003	0.066	0.003	0.030	0.044	0.008
	(0.126)	(0.139)	(0.136)	(0.072)	(0.068)	(0.029)
Post	0.131+	-0.208**	0.176**	-0.139***	-0.094**	-0.026**
	(0.097)	(0.105)	(0.089)	(0.041)	(0.041)	(0.013)
Lag_Post (1 year post-treatment effect)	-0.092	0.089	-0.077	0.068*	0.051	0.015
	(0.104)	(0.091)	(0.069)	(0.036)	(0.035)	(0.012)
Observations	11495	15242	15242	19391	19391	19391
R-squared	0.40	0.45	0.40	0.40	0.41	0.17

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. Regressions in columns (1) to (3) have dependent variables expressed in natural logs and include month-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) to (6) 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.

Survey design issues

As mentioned earlier, we built a panel dataset at the village level using the PLSMS for years 1997 and 2000 and the ENAHO for years 2001 through 2007. Although both surveys are representative at the national level and all of our regressions are weighted using the inverse of sampling probability to control for survey design, cannot ignore the issue that the sampling framework was different for both surveys.11 Therefore, in order to test for the robustness of our results, we re-estimate model (14) using only the observations coming from the ENAHO survey (years 2001 through 2007). Table 15 displays the estimation results. Estimated impacts using the trimmed sample are virtually the same as the estimated effects coming from the complete dataset. Therefore, it appears that survey design is not an issue of concern in our dataset.

Table 15: Estimated effects dropping years 1997 and 2000

Panel A: Agricultural outcomes				
Dependent Variable (in natural logs):	Value per kg. sold	Production in kgs.	Agricultural costs	Profitability value/costs
	(1)	(2)	(3)	(4)
Post	0.121+	-0.068	-0.203*	0.180**
	(0.083)	(0.097)	(0.104)	(0.089)
Observations	11013	14657	14657	14657
R-squared	0.39	0.51	0.43	0.40
Panel B: Child outcomes				
Dependent Variable:	Market work	Agricultural work	Wage work	School enrollment
	(1)	(2)	(3)	(4)
Post	-0.150***	-0.103**	-0.022*	0.002
	(0.041)	(0.041)	(0.012)	(0.017)
Observations	18254	18254	18254	18112
R-squared	0.44	0.44	0.18	0.73

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. All regressions in Panel A include month-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 Panel B include all previous controls plus child characteristics (sex and age). + significant at the 15% level; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

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

[11] The PLSMS had their sampling framework in the 1993 Peruvian Census, while the ENAHO (2001-2006) had their sampling framework in a pre-census conducted during 1999-2000. Finally, the ENAHO 2007 had the 2005 Peruvian Census as sampling framework.

a 2 hour travel time range to the nearest phone. Then we estimate model (14) allowing for differential impacts among villages situated within 30 minutes travel time intervals.

Table 16 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.

Table 16: Spillover effects

Dependent Variable:	Value per kg. sold	Agricultural costs	Profitability value/costs	Market work	Agricultural work	Wage work
	(1)	(2)	(3)	(4)	(5)	(6)
Post - 30 minutes	0.149*	-0.213**	0.178**	-0.137***	-0.092**	-0.021*
	(0.087)	(0.105)	(0.089)	(0.041)	(0.041)	(0.012)
Post - (30 ; 60] minutes	-0.120	0.200	0.205	0.107	0.116	-0.015
	(0.199)	(0.168)	(0.143)	(0.115)	(0.115)	(0.017)
Post - (60 ; 90] minutes	-0.313	0.182	0.179	-0.044	-0.038	-0.003
	(0.197)	(0.213)	(0.120)	(0.107)	(0.106)	(0.015)
Post - (90 ; 120] minutes	0.298	-0.269	0.343	-0.079	-0.125	0.032
	(0.264)	(0.253)	(0.224)	(0.078)	(0.085)	(0.021)
Observations	18329	24304	24304	29992	29992	29992

Estimated standard errors clustered at the village level in parentheses. Weighted regressions using the inverse of sampling probability to reflect survey design. Regressions in columns (1) to (3) have dependent variables expressed in natural logs and include month-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) to (6) include all previous controls plus child characteristics (sex and age). * denotes significance at the 10% level; ** denotes significance at the 5% level; *** denotes significance at the 1% level.

Event studies

In order to disaggregate the before-after effects previously estimated into bimonth-by-bimonth effects, we add flexibility to model (14) by estimating regression equations of the following form:

$$O_{ijt} = \alpha_j + \phi_t + \sum_{-6}^{+7} \beta_p D_{jp} + X_{ijt}^{'}\gamma + Coast_j f(t) + Highlands_j f(t) + Jungle_j f(t) + \varepsilon_{ijt} \quad (17)$$

where D_{jp} is an indicator for the pth bimonth after the phone became operative in village j (where p=0 is the bimonth in which the phone became operative).[12] We omit the $D_{j,-1}$ indicator from the regression, so our estimates of the

[12] Notice that we use observations from households surveyed within a window of one year before and one year after the installation of the phone.

coefficients β_p are interpreted as the mean of the outcome variable relative to the bimonth before the phone became operative. All other variables are defined as in (14).

Estimated β_p coefficients for the value per kilogram of agricultural production sold along with their 95% confidence intervals are shown in Figure 5. Notice that point estimates bounce around zero before the intervention and are all insignificant. This observation gives further support for the validity of our approach, since we do not see evidence of any trend prior to the installation of the phones. Then, starting in the bimonth the phone became operative, estimated impacts become positive and increasing over time (although power is low). A similar pattern is observed for agricultural profitability (measured as the ratio of total production value to costs) in Figure 6. No significant point estimates are found before phone installation, while positive and increasing impacts are observed after the intervention.

Figure 5: Value per kilogram sold

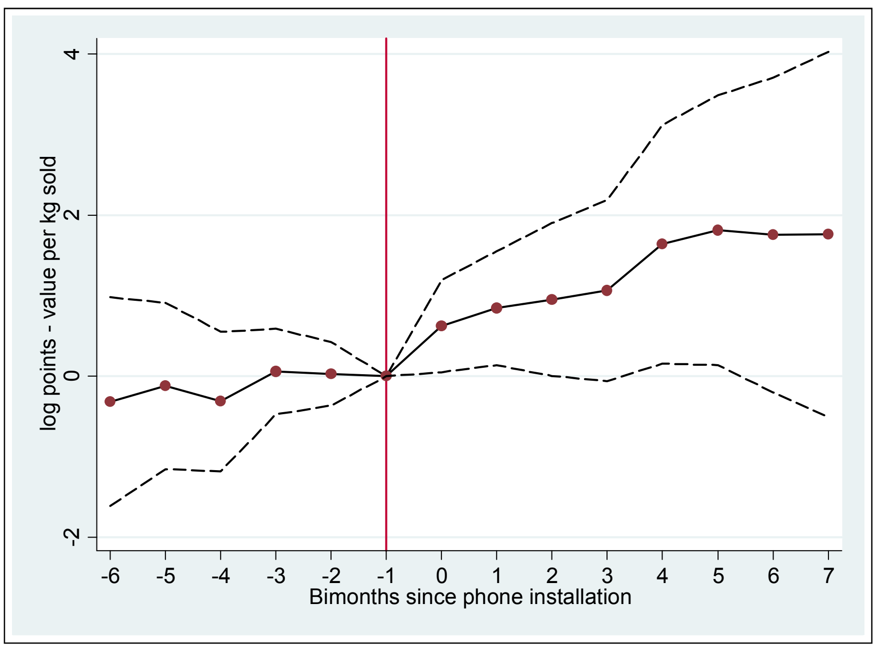
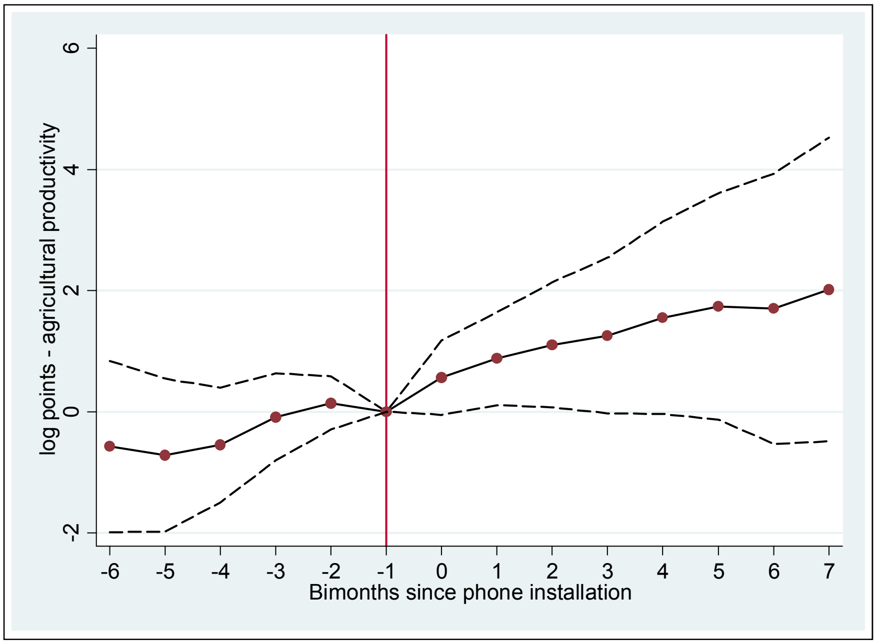


Figure 6: Agricultural profitability



Child labor effects are shown in Figures 7 and 8. Figure 7 plots estimated β_p coefficients for the probability of reporting any type of market work as the main activity. We observe insignificant estimated coefficients prior to the intervention, followed by negative, decreasing and significant estimated impacts starting one bimonth after the phone is installed. Figure 8 shows similar estimated impacts for the probability of reporting agricultural work as the main activity.

Figure 7: Child market work

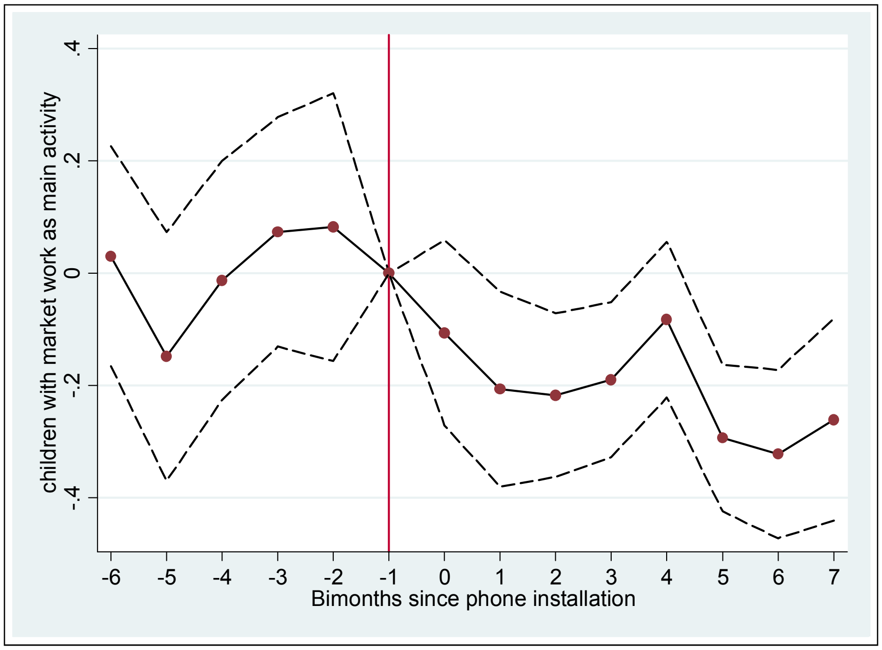
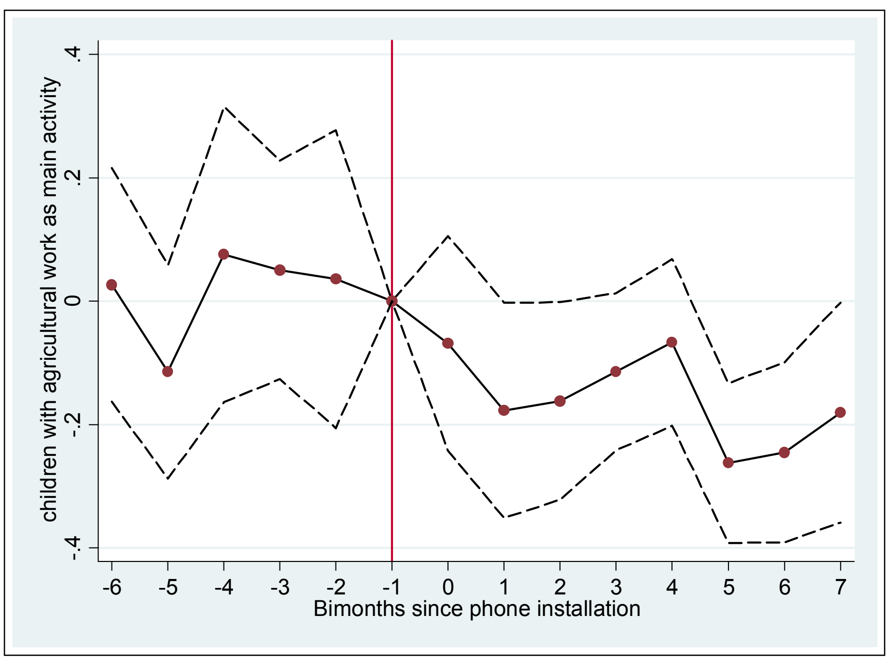


Figure 8: Child agricultural work



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% following the installation of the phones, while agricultural costs were reduced by 23.7%. These impacts together imply an increase of 19.5% in agricultural profitability. Moreover, this income shock was translated into a reduction of child market work equivalent to 31.9% of baseline labor supply and a reduction in child agricultural work of 26.3%, 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. Differences in effects by population density are also consistent with the notion that areas with higher potential labor supply to substitute for child labor display greater impacts on children's time allocation. There are differential effects by child gender and by education of the head of household, suggesting that child labor is reduced more for groups with higher ex-ante incidence of child labor. 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, event studies analyses show that no pre-existing trends were present with respect to the outcomes of interest and that the estimated impacts became significant as a result of phones introduction.

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* Vol 2, Iss. 3: 46–59.

Beegle, K., et al. 2006., Child labor and agricultural shocks. The Journal of Development Economics 81: 80-96.

Brown, J. R., and 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 Perụ. Journal of Development Economics 86: 164–18.

Dehejia, R. and 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. Volume
53, Number 4, pp. 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. and 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. and 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, 455–480.

Fiszbein, A. and 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 Vol 2, Iss. 3: 22–45.

Granger. C. W., 1969. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica 37, 424 – 438.

Ilahi, N., 2001. Children's work and schooling: does gender matter? Evidence from the Peru LSMS. World Bank Policy Research. Working Paper, vol. 2745.

Jensen, R., 2007. The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. Quarterly Journal of Economics, August 2007, Vol. 122, No. 3, Pages 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: 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, 339–356.

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

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

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