The Crop Connection: Impact of Cell Phone Access on Crop Choice in Rural Pakistan *

Saher Asad †

20th August 2019

Abstract: Cash crop production is important for economic development. However, cash crops are often perishable, and therefore suffer from high post-harvest losses when market linkages are weak. Can cell phones help farmers overcome this risk of producing cash crops? Using data from rural Pakistan, I estimate the impact of cell phone access on production decisions of farmers. For identification, I exploit a policy that restricts cell phone coverage from villages within 10 km of the Indian border. Regression discontinuity estimates show that cell phone access causes an increase in the probability of producing perishable crops, improvement in farmer-trader coordination and reduction in post-harvest losses.

Keywords: Cell Phones, Crop Choice, Pakistan, Agriculture, Risk, Post-Harvest Losses, Coordination, ICTs and Development
JEL Classification: Q13; O13; O12; O33

*I gratefully acknowledge funding for this research from a five year William J. Fulbright Ph.D. Fellowship and research grants from Institute of International Economic Policy and Sigur Center for Asian Studies at GWU. I am indebted to my dissertation committee, Stephen Smith, James Foster and Ram Fishman for all their encouragement, advise and patience during the course of this project. This research greatly benefitted from discussions with Jenny Aker, Quamrul Ashraf, Sarah Baird, Tony Castleman, Shawn Cole, Oliver Vanden Eynde, Bjorn-Soren Gigler, Raymond Guiteras, William Jack, Remi Jedwab, Molly Lipscomb, James Robinson, Monica Singhal, David Weil and Chris Udry. I thank all participants at ABCDE 2016, NEUDC 2015, PODER Summer School at PSE, IFPRI Seminar, WADES 2014(University of Maryland), IPWSD(Columbia University), GWU Trade and Development Seminar, SESRIC Seminar, GWU Development Lunch, SAGE GWU Seminar and Sigur Center Fellows Roundtable for comments and suggestions. I am grateful to ACO and PBS Pakistan for sharing their data; to my data collection team in Pakistan for assisting in household survey, and to Tasneem Asad for assisting with agronomic experiments. I am thankful to Asad Elahi, Zafar Altaf, Muhammad Mian Javed, Parvez Iftikhar and Muhammad Akram Khan in Pakistan for extensive discussions on data collection and institutional details. This project would not be possible without the hospitality of agricultural households and market traders who welcomed me and my data collection team at all times. All errors are my own.

†Assistant Professor of Economics, Lahore University of Management Sciences. Email: saher.asad@lums.edu.pk

" Before I had a cell phone I harvested my crop and then had to wait for a trader to buy my crops; now I talk to the trader and harvest my crops when he will buy it."

(Farmer in Rural Pakistan)[1]

1 Introduction

Economists have long believed that shifting to cash crop production is very important for reducing poverty in developing countries.[2] Cash crops are often highly perishable and experience rapid rates of spoilage when storage technology is dated and market linkages are weak [Duke & Ducellier, 1993]. As a result, in developing countries, farmers growing cash crops are at a risk of experiencing high post-harvest losses.[3] It can be hypothesized that this risk deters the farmers from growing the high-return cash crops. Can cell phones help the farmers mitigate the risk of incurring post-harvest losses by improving buyer-seller coordination?

In this paper, I, to the best of my knowledge, provides novel estimates to show that access to cell phone coverage improves farmer-trader coordination, resulting in farmers shifting towards growing and successfully selling the perishable cash crops and thus experiencing positive impact on their income and consumption.

In developing countries, where agriculture constitutes a major share of GDP, the choice of crops planted by farmers is especially important. The production choices of farmers are conditioned by the risk environment they face [Food and Agriculture Organization, 2014]. In developing countries farmers are faced by risks in pre-harvest as well as post-harvest period. [Grolleaud, 2002]. While both types can impact the production choices of farmers; the focus of this paper is on studying the role of post-harvest risks. For the perishable crops, post-harvest losses are critical as they can impact the profitability of crops.

[1]Translation from primary research conducted by author.

[2]For general discussion see World Bank [2012], International Food Policy Research Institute [2013] and Food and Agriculture Organization [2014].

[3]For details see National Research Council Board on Science and Technology for International Development [1978]

One plausible post-harvest risk faced by farmers in developing countries is that of losing a major portion of perishable crops to spoilage while in storage. Farmers sell their crops to traders in the agricultural wholesale market which is commonly known in South Asia as the *mandi*. The traders in the *mandi* due to storage related constraints, have limited purchasing capacity for perishable crops. In the given circumstances, it is hypothesized that both the farmer and the trader have a strong incentive to coordinate. One possible mechanism for achieving coordination can be through pre-arranging a sale date and then harvesting crops close to this date. This can be beneficial for the farmer as he has lower post-harvest losses. The trader can also benefit as this allows him to prevent having below capacity days, leading to higher income over season.

Despite the presence of strong incentive to coordinate, it may not be achieved due to the high cost associated with it. In rural areas of developing countries, farmers spend a significant amount of time working on the farm during the harvest period, so they lack the time to travel to meet with the farmers; this can be hypothesized as a primary reason for being unable to plan an advanced sale date. The process of coordination involves multiple interactions as the date may change due to conditions of both farmer and trader. Can the cell phone help farmers and traders coordinate better?

In the past decade, rural cell phone density has grown tremendously in developing countries. This has provided a fast and generally affordable source of information for people living in rural areas of developing countries. In this paper I exploit the spatial expansion of cell phone coverage in Punjab, the hub of Agriculture in Pakistan, which provides the context to test its impact on farmers' crop choice and buyer-seller coordination. Cell phone coverage started expanding into the rural areas of Pakistan in 2000. Naive estimates obtained by applying Difference-in-Difference (D-in-D) strategy to country wide data and Triple Difference to study districts, show that access to cell phone coverage has a positive impact on probability of growing perishable crops.

Cell phone towers are not placed randomly making it difficult to estimate the causal impact of access to cell phone coverage on crop choice. To deal with these issues, my preferred empirical strategy relies on making use of the following unique policy. As a result of security concerns, the Government of Pakistan declared area within 10 km of International border with India as the "Dead Zone", area without cell phone coverage.[4] The presence of this restriction allows the use of a Spatial Regression Discontinuity Design to estimate the causal impact of cell phone access on crop choice.

The data utilized to implement the aforementioned econometric techniques exists at two levels, both at the village and household level. A village census from 2008 provides information on every village in the country. By combining this data with spatial information, I can accurately determine whether or not a particular village is in the "Dead Zone". Using this I estimate the causal impact of cell phone access on crop choice at the village level. Due to the presence of a negligible level of noncompliance[5], this paper applies the Fuzzy Regression Discontinuity Design (FRD) to village level data using method of Dell [2010].

The village level dataset is complemented by a detailed new household survey that I conducted in 2013 of 450 agricultural households located in 30 villages in 5 districts in Punjab, which are located next to the International Border with India. I utilize the household data to test for the different plausible mechanisms through which cell phone access can impact crop choice. Inclusion of additional data sources such as market location, prices, optimal plantation dates for each crop, as well as perishability ranking[6] in the harvest period add to the strength of analysis. I then utilize the household survey to test the impact of cell phone access on crop choice using the Sharp Regression Discontinuity Method by Dell [2010]. In both the fuzzy and sharp cases, I test for several specifications with polynomials in distance to restriction and latitude and longitude.

[4]Enforcement of this zone is done by the strategic placement of cell phone towers as well as the placement of signal jamming devices.

[5]Noncompliance in villages here refers to villages lying in restriction receiving cell phone coverage and vice versa. The data shows that this is less than 5%.

[6]The perishability ranking is constructed from agronomic tests I conducted while simulating field conditions

I find that the results from both the village level and household level data are consistent with the original hypothesis that access to cell phone coverage leads to farmers moving towards growing highly perishable crops. In case of the village level data, the FRD estimates show that access to cell phone coverage increases the probability of growing the perishable crops by 0.23 to 0.26.[7] SRD results from household data show that access to cell phone coverage increases the share of land allocated to extremely perishable and highly perishable crops by 23-27% and 16-18% respectively.[8]

I hypothesize that there are atleast three potential mechanisms through which access to cell phone coverage can impact the production choices of farmers. First is through improvement in buyer-seller coordination, resulting in lower post-harvest losses, making perishable crops more profitable. SRD results show that this mechanism is strongest for most perishable crops. Second, access to cell phones improves farmers' knowledge of the optimal plantation date and this improved knowledge has a greater impact on perishable crops compared with the less perishable ones. SRD results show that the impact on accuracy of plantation dates and crop yields is statistically significant for the extremely and highly perishable crops but is not economically significant. Third, cell phone coverage increases the price of perishable crops received by farmers more than that of less perishable crops. SRD results reveal that the impact of cell phone access on price while positive, however, is not significantly different for categories of crops along the perishability dimension.

The analysis of the three mechanisms shows that only the buyer-seller Coordination mechanism is both statistically and economically significant. The paper then examines the eventual impact on households' income and consumption. SRD estimates suggest that access to cell phone coverage increases farmers' agricultural income and household consumption by 10-15% and 8-10% respectively.

[7]Due to data limitations in the village level data, the crops are categorized as perishable(combines extremely and highly perishable) or non-perishable(also referred to as less and least perishable).

[8]The range of the estimates comes from looking at crops with varying levels of perishability from applying different polynomials for the RD estimates.

This paper makes a contribution to literature in several ways. First, this to the best of my knowledge, is the first study which examines the role of post-harvest risk in determining production choices of farmers. Previous studies on post-harvest losses have focused on measuring them in context of grains.[9] While post-harvest losses are also important for grains due to the presence of diseases and pests, their role in shaping incentive to produce perishable crops can be much larger due to the naturally higher rate of respiration and transpiration. The focus of research related to agricultural production decisions and risk has been limited to pre-harvest risks.[10] Second, in this paper I provide first estimates for the impact of cell phone access on buyer-seller coordination, which I hypothesize is the primary mechanism through which cell phones impact crop choice. Previous research evaluating the impact of Information and Communication Technologies (ICTs) on agriculture have looked at mechanisms related to market price and weather related information.[11]

2 Context

The decision related to choice of crops is one of the most crucial decisions for the farmers living in rural areas of Pakistan. The region of study in this paper is the province of Punjab. On average farmers in Punjab grow 4 to 6 crops in a year and 2 to 3 crops in a season. This provides sufficient range and allows enough decision making to test the impact of cell phone access on production choices.

Previous research related to agriculture in Pakistan has not focused on the importance

[9]For studies related to post-harvest losses see Kaminski & Christiaensen [2014], Food and Agriculture Organization [2014], International Food Policy Research Institute [2013], Grolleaud [2002] and Oehmke [1992].

[10]For more details on weather based agricultural risks in developing countries' agriculture see De Janvry & Sadoulet [2006], Dercon [1996], Fafchamps [2003], Food and Agriculture Organization [2014], Gine & Yang [2009], Karlan et al. [2014], Dercon & Krishnan [1996], Macours [2013], Rosenzweig & Binswanger [1993], Singh et al. [1986], Suri [2011], Cole et al. [2013], Vargas Hill & Torero [2009], Vargas Hill & Ciceisza [2012] and Cole et al. [2014].

[11]For complete review of studies on this topic see Aker [2010], Aker & Fafchamps [2013], Bayes [2001], Chong et al. [2009], Cole & Fernando [2012], Curtois & Subervie [2014], Fafchamps & Minten [2012], Futch & McIntosh [2009], Goyal [2010], Jensen [2007], Jensen [2010], Labonne & Chase [2009], Mitra et al. [2013], Muto [2009], Parker et al. [2013], Svensson & Yanagizawa [2009] and Wellenius [2002].

of information and communication networks. Based on the data collected in the household survey, agriculture extension services reach out only to a negligible minority. In the presence of such services, their role is limited to only certain times within the crop cycle. In particular, findings from author's conversations with the farmers revealed that they face very high post-harvest losses due to lack of buyer-seller coordination. The root of these problems can be linked to the structure of the Pakistani whole sale markets also known as the mandis.

A Pakistani mandi is a central market place where farmers come and sell their crops. Mandi is the point where farmers or the middlemen interact with the traders. The traders purchase these goods from the farmers, and then sell them to retailers or actual customers.[12] Although mandis operate in different parts of the world, and are particularly very common in South Asia, the farmer-trader relationship in the Pakistani mandi has several important features relevant to this paper.

In a Pakistani mandi there are at most a few traders per crop. In every mandi there exists an association of all the traders in that mandi. Any entry and exit of traders from this market is approved and regulated by this association. If more than one trader exists per crop they are commonly from the same family. However it is safe to assume that the number of traders per crop is very small. Interviews with the traders and the farmers suggest that traders refrain from purchasing more than one good as they have full knowledge of its quality. Sometimes they purchase more than one good if the goods share comparable features. For example, potatoes and onions both are tuber root vegetables and have similar features. Therefore the traders can evaluate the quality of the vegetables easily. The Purchasing capacity of the trader is fixed. A trader mentioned during a field interview that their purchasing capacity of the is constrained due to dated storage technology as well as scheduled and unscheduled power outages rendering existing storage unviable.

There is only one mandi per district, therefore all farmers from a district visit the same

[12] Most people purchasing at the mandi are retailers, relatively fewer people are seen at the mandi as the mandi is often located in places relatively remote areas, farther away from city as they require a large piece of open land.

mandi. Structured interviews with the farmers suggest that this is due to several reasons. First, the buyer-seller relationships go back for several generations and hence traders only trust the farmers they know. Second, mandi in the neighboring district is often sufficiently far so that it discourages the farmers from taking their crops to mandi in the neighboring district.

Once the harvest is completed, the farmers hire a truck to bring their harvested crops to the mandi. The trucks in which the crops are brought to the market are very basic and do not have any temperature control options. Most of the trucks are open on the top, however, some trucks are covered with a basic permeable cloth. The mandi operates between the hours of 6 am to 7 pm. Most trading between farmers and traders occurs at the start of the day.

Farmers with cell phone access can pre-arrange a sale date with the trader. Close to the harvest period there is continuous communication between farmer and trader as the sale date may fluctuate. Due to the uninterrupted nature of this communication, it is not possible to have a pre-arranged sale date if the farmer does not have cell phone access. If the farmers do not have a pre-arranged sale date, they have to wait in the line. The trader will only purchase if he has capacity left after purchasing from those with a pre-arranged sale date. If the trader does not buy their crop, the farmers will take it back to their village and then visit mandi the next day. During this time the perishable crops experience post-harvest losses.

The structure of the Pakistani mandi is extremely critical to influencing the incentives to growing perishable crops. Perishable crops also have some other features which can make a strong link between crop choice and cell phone access. These include which include the price received by farmer as well as weather information which are discussed in literature to be known to contributing to farmers growing perishable crops. The highly perishable crops are much more sensitive to dates of plantation. Every crop has an optimal period of plantation, which changes frequently based on biological conditions. If crops are planted with in this period of plantation farmers get higher yield as compared to if they plant outside this period.

Inaccurate dates of plantation can lead to lower yields, particularly in the highly perishable crops. This optimal period of plantation changes every year based on the changes in weather and other important natural factors.

3 Data

To conduct the econometric analysis this paper employs several sources of data. In particular there are two distinct parts to the analysis. The first part consists of village level data which is made up of several different sources of data. The second part involves the use of household level data.

3.1 Village Level Data

The primary source for the village level data for this analysis is the micro data from the Mouza (Village) Census 2008. For the sake of simplicity, this paper uses the word mouza or village interchangeably throughout the paper.[13] The Mouza Census is carried out by the Agriculture Census Organization of Pakistan (ACO) every five years. Agriculture Census Organization of Pakistan [2008]. Mouza Census provides data on major crops grown, details on the distance from different services, as well as telecommunication services. These additional questions provide the relevant data for conducting the analysis for this paper.[14]

In addition to the Mouza Census 2008 data, this paper also uses the Agriculture Census 2000 micro data. No direct identifier links together the Mouza Census 2008 to the Agriculture Census 2000, the author conducted matching of the two using village names and the spatial information separately available. A detailed Appendix explains how this matching

[13] According to The Agriculture Census Organization, mouza, village, deh and killies are equivalent and are treated as the same unit. It is important to note that each mouza can have several abadies or sub-abadies, however throughout the paper, the unit of analysis is mouza.

[14] The dataset has information on all Mouzas in the country except of Mouzas from Bajour Agency, North Waziristan Agency, South Waziristan Agency, F.R Kurram, Kurram Agency and Orakzai Agency. All the villages were covered irrespective of the status, however only limited information was collected for urban, forest and un-inhabited mouzas.

was conducted and how variables were constructed while maintaining comparability across datasets.

The paper also makes use of detailed village level location information from the Mouza Boundary shapefile. This data source will help with the construction of the spatial discontinuity variable, which will be described in much more detail later in the paper. The data source is the Mouza Boundary Shapefile. The data described however does not have any direct links to the Mouza census data. All results presented in the paper are based on the matching performed by author in consultation with the relevant authorities. The details of the matching procedure employed are presented in the detailed Appendix.

3.2 Household Level Data

To obtain household level data, the author conducted a household survey in 2013 which customized random sampling around the 10 kilometers(km) restriction. There could be several concerns that villages very close to the Indian Border are not comparable to the villages just outside of the restriction boundary, making the 10 km radius too wide to estimate the causal impact of the restriction. To deal with this issue, the study zone is restricted to 5 km around the restriction. The data showed that 5 percent of the villages do not comply with the restriction status. To deal with this, the non-complying villages were dropped before sampling.[15] From the complying list of villages, the author randomly sampled 6 villages in each of the 5 districts, where 3 villages lie in the restriction zone (5-10 km) and 3 villages lie in the non-restriction area (10-15 km).

The next step involved the sampling of households in each of the villages. To sample the households, a list of all the land operating households was constructed in each village. From this list a random sample of 15 land operating households was drawn in each village.

[15]The villages that had non-compliance were the ones with over lapping area in restriction and non-restriction zone. I used the village level data to study the difference in complying and non-complying villages and I find that the only significant predictor of non-compliance is that proportion of area overlapping between restriction and non-restriction area.

The definition of land operating households was limited to the households that either owned land or operated land under a rental or share cropping arrangement. This provided a total sample size of 450 households.[16] The enumeration was conducted with help of a team of 10 local graduate students of economics and statistics, who received intensive training from me.

The purpose of collecting household data is to identify the the key mechanisms through which cell phones can impact crop choice. The questionnaire adopted an approach where modules were designed to follow the decision-making processes of farmers from sowing to selling. In addition to the data about each stage, farmers were asked how they obtained information to make decisions during each stage. Farmers were also asked about the dates at which they executed each stage, which was validated using a receipt checking process.[17] Further, the questionnaire also collected a retrospective panel data on crop choice. As crop choice is one of the most significant decisions of a farmers process, he is not likely to forget the year in which he switched between crops, hence making error in retrospective information related to crop choice unlikely. In fact during the survey farmers also reported that they were aware of the key crops their ancestors grew. In addition the use of hand held GPS units was employed to collect the geo-spatial information on location of households and other key features in their proximity.

3.3 Market Price Data and Bench Marking of Optimal Plantation Dates

In addition to the survey and census data, other data sources are employed to improve the analysis. One is the market data, which includes information on market prices. However

[16] More details on sampling of villages and households for the household survey available from author.

[17] The receipt checking process involved verifying several important dates which included sowing, fertilizer application as well as harvesting. Farmers in Pakistan maintain either receipt or registers which have information of these dates. This is due to the fact that in all the stages either farmers have to purchase the relevant items e.g. seeds, fertilizers etc or they have to hire labor in the process. In order to make any of the above transactions farmers need to maintain records as contractual enforcement is not possible without that. If the validity of the transaction is later questioned, the farmer can present relevant paper to the court of village elders. The date of

this data is a static snapshot of the market prices. To complement this information on weekly crop prices which are collected by the Government for CPI (Consumer Price Index) and WPI (Wholesale Price Index) calculation are also utilized. To obtain information on benchmarked or optimal plantation dates for each crop, the author conducted structured interviews of local researchers and agriculture experts. These dates are important as the farmer plantation dates are compared to these dates to measure the accuracy of the farmer's plantations decision. Based on these conversations with the local experts, over the years weather and other natural conditions have changed and hence every year there is a new interval of benchmark dates. If the farmer plants the crop in this benchmark period they are likely to get higher yields than if they plant too early or much later after the benchmark period. In particular it can be hypothesized that the more perishable the crops, the more sensitive their yields are to these benchmarked dates.

3.4 Construction of Perishability Ranking

The construction of the perishability ranking posed a challenge because the ranking had to be constructed based on field conditions of the area. Previous rankings were often established in forms of range of shelf life and under optimal conditions. Similarly, some of the crops become less perishable after being processed but were highly perishable in the harvest period. For instance, sugar cane must be processed within 48 hours of harvest or fresh turmeric is considered one of the most perishable crops in harvest period while dried turmeric can last a very long time. The author supervised an experiment which simulated field conditions and monitored 20 units of each of the 18 crops in order to establish the ranking.[18] for 20 days in Pakistan.[19] All units were weighed and measured at the baseline and then one unit

[18]These 18 crops were chosen for ranking as these are all the crops that were found in the household survey data.

[19]The experimental conditions were set in consultation with local agriculture experts to mimic the field conditions faced by small farmers rather than optimal conditions. All measurements were conducted using the scientific instruments and standards. More details on the experiment can be provided upon request.

was measured and weighed every day until the end of the experiment.[20]The results of the simulated field conditions were then used to construct ranking the perishability of crops at harvest. The ranking was constructed as:

Extremely Perishable: Tomatoes, Orange, Mangoes, Corn, Sugar Cane

Highly Perishable: Onion, Garlic, Potatoes, Taro, Peas, Fresh Tumeric

Least Perishable: Millet, Feed, Sorghum, Rice, Wheat, Cotton

This ranking serves as the perishability ranking of crops throughout the paper. The paper will refer to all crops as belonging to these levels, where the above table provides the different levels, for the rest of the paper.

4 Identification with Spatial Regression Discontinuity: "Dead Zone"

Over the past decade, Pakistan has experienced substantial growth in cell phone coverage as well as penetration rate. Cell phone coverage was introduced to rural areas of Pakistan after 2000. Pakistan has been ranked as the country with 4th most affordable cell phone tariffs in the world. [World Economic Forum, 2012] This proliferation in growth accompanied by the modest tariffs suggests that there could be a significant impact on decisions of farmers. Currently 5 different mobile phone companies provide coverage to urban and rural population in Pakistan. Initially only urban areas received coverage and till about early 2000, no rural areas had any cell phone coverage. Eventually, cell phone coverage started growing in the rural areas of Pakistan, and in 2006 Universal Service Fund of Pakistan was set up to further facilitate this process.

Access to cell phone coverage has also been the first source of information and communication technology for people living in rural areas of Pakistan. The landline coverage has

[20] After baseline measurement, only one unit was measured and weighted everyday to avoid the contamination due to constant measurement. For example if a unit of tomato is measured everyday then it will become more pulp just due to being constantly measured.

been relatively low in the rural area. In places where the access node was available the landline density has remained very low. In Pakistan acquiring a landline connection requires a very lengthy, difficult, time-consuming and expensive procedure. The tables on Summary Statistics show that level of landline density is very low in rural Pakistan.

Cell phone towers are not placed randomly; hence, there is a need for identifying an exogenous source of variation in cell phone coverage. Due to security concerns, the Government of Pakistan created a cellular dead zone of 10 km around the International Border with India.[21] Despite the growth of cell phone coverage in Pakistan, it was decided early that cell phone coverage will not be provided in 10 Km of International Border with India due to security concerns.[22] Although the Government has officially created a very strict restriction, data shows that the restriction suffers from some non-compliance close to restriction due to overlapping area in the buffer and non-buffer zone. Particularly, the 10 km restriction is arbitrary and also not connected to any other restriction.[23] The author matched all villages in 5 districts of the 20 km of India-Pakistan Border to data from the Mouza Census, to construct this measure and also to generate the coverage maps. The structure of this matching is present in Appendix.[24]

To implement the spatial discontinuity design, ArcMap was utilized to create the 10 km restriction using the buffer command. Based on this for each village a perpendicular distance was estimated from edge of the village boundary to the restriction line. Figure 1 in the list of figures shows the map of the study districts. Figure 2 shows that there is

[21]This restriction and identification strategy is not just data driven as shown by the maps, but I have also validated the existence of this restriction by conducting anonymous structured interviews of several the different stakeholders involved in the provision of cell phone services in rural areas of Pakistan.

[22]The decision to not provide coverage in the 10 km area was decided early and hence these areas never received coverage.

[23]The size of the no mans land is 500 meters in the radius of border, which is much narrower compared to the 10 km signal restrictions. The officials that the author consulted, refer to this 10 km zone as the "Buffer Zone", "The Dead Zone" as well as "No Signal Zone".

[24]It is not possible for people in Pakistan to purchase an Indian sim card. Second due to technical reasons the cell phones used in Pakistan are not able to accept the Indian sim card. Third people in Pakistan have no incentive to purchase or use an Indian sim card because if they used it they would have to pay international charges which are very high.

sudden change in cell phone coverage at the restriction line. As seen from the figure there is some non-compliance around the restriction. However, this non-compliance is driven by the villages that partly lie in the restriction zone and partly lie in the non-restriction zone. The percentage of villages that have non-compliance is 5 percent.

For robustness, the observations are trimmed to only include villages lying within 5 km around the restriction. Specifically, this is to address any concern that the areas in the immediate neighborhood of the border may not be very similar to the villages in 10-20 km range. This sample also serves as the sampling frame for the household level study.[25]

5 Empirical Strategy and Specification

The following specification is adopted to study the impact of cell phone access on crop choice at either household or village level:

$$Outcome_i = \alpha_0 + \alpha_1 cellphone_i + \alpha_2 X_i + \epsilon_i \tag{1}$$

The subscript "i" represents the household or the village depending on the data used. The value of x ranges from 1 to 4 based on the perishability of crop. Outcome can represent the binary crop choice variable from village level data or the area under that crop from the household level data. The cell phone variable here is a binary variable which equals 1 if the village has cell phone coverage and 0 otherwise.

The covariates included in X for the village level case are percentage of area cultivated, pre-coverage distance from pucca road network, wealth measures like roof structure of majority of households in the village, elevation, access to agricultural credit and access to irrigation . The covariates included in X for the household level case are percentage of area

[25] Although the restriction is arbitrary and not connected to any other restriction, there may be some concerns with regard to the gradient of cell phone coverage. In order to look at that the cell phone coverage in villages lying in 20-30 km of the border was examined and then compared them to those lying in 10-20 km. The results show that no significant difference exists in cell phone coverage in these two areas. These additional results are available in an online appendix.

cultivated, pre-coverage distance from pucca road, household asset ownership, education, access to agricultural credit, household size, non-agricultural sources of income and access to irrigation. The given control variables were selected as these variables in particular may effect crop choice without being outcomes in themselves. This is important because if the controls can be outcomes in themselves then they can also bias the results. In addition in both the household and village level models, a full set of district fixed effects, crop fixed effects and district-crop fixed effects are included. All standard errors are clustered at union council level in village level data and neighborhood level in household level data.

The cell phone coverage variable is endogenous and to deal with this issue a FRD approach is applied in village level data case and SRD in the household level data case.

5.1 Fuzzy Regression Discontinuity

The FRD is applied in the village level data. A Semi-parametric FRD estimation method is applied due to sample size concerns. This is the case in studies utilizing a geographic regression discontinuity as implementation of non-parametric techniques requires a larger sample size around the threshold. [Imbens & Lemieux, 2008] The observations are much more uniformly distributed in cases of geographic discontinuities. Although it is not possible to employ the purely non-parametric estimation here, the semi-parametric case with the number of observations limited to 5 km around the restriction is considered. Using technique of Dell [2010] with quadratic, cubic and quartic polynomials in Euclidean Distance from restriction[26] as well as latitude and longitude, results are presented for all 6 specifications.

The second stage equation is given by:

$$Outcome_j = \alpha_0 + \alpha_1 cellphone_j + \alpha_2 X_j + f(distancefromrestriction) + \epsilon_j \tag{2}$$

The first stage equation can be expressed as:

[26] Throughout the paper the terms distance from restriction and Euclidean distance from restriction are used interchangeably

$$Cellphone_j = \beta_0 + \beta_1 LieinRestriction_j + f(distancefromrestriction_j) + \zeta_j \qquad (3)$$

Figure 3 shows that the probability of growing extremely and highly perishability crops increases at the deadzone boundary. A necessary condition for the discontinuity to be valid is that no other covariates should change at the threshold. The summary statistics provided in Table 1 for the village level data for observations lying in 10 km and 5 km band around restriction line show that the covariates are not different between villages with and without restriction. Furthermore, there are no significant differences between covariates as the band around the restriction narrows. Another condition is that the treatment variable (cell phone coverage) should jump at the 10 km boundary. The map of cell phone coverage presented in Figure 2 shows that cell phone access changes discontinuously at the cut off. Additionally it is important to test for the density discontinuity to check for any data manipulation around the threshold. The McCrary density test is applied to test for this assumption. The result from the test is plotted using the Stata Code due to McCrary [2008]. Figure 4 shows that density is smooth at the threshold for the Euclidean distance from restriction.

5.2 Sharp Regression Discontinuity

For the household data, sharp regression discontinuity design is applied. There are a total of 450 households in the data where 225 were sampled from within restriction zone (5-10 km from border) while the other 225 households were sampled from outside the restriction zone (10-15 km from the border). Semi-parametric approach with quadratic, cubic as well as quartic polynomials in euclidean distance from restriction as well as the longitude and latitude is applied to the household data.[27] The sample in this case is already restricted to 5 km around the restriction line as the sampling was only performed in this zone. The results

[27] Due to sample size limitations the semi-parametric approach applied in village level data is also applied to household level data.

are presented for all six specifications. The estimation equation here becomes:

$$Outcome_j = \alpha_0 + \alpha_1 Cellphone_j + \alpha_2 + \varphi(distancefromrestriction_j) + \alpha_3 X_j + \epsilon_j$$

Figure 5 shows that the proportion of area allocated to growing extremely and highly perishable crops jumps discontinuously at the cut off. An important condition for the discontinuity to be valid is that no other covariates should change at the threshold. The summary statistics provided in Table 2 for the household level data show that the covariates are not different between households with and without cell phone access. The paper also tests for density discontinuity to check for any manipulation around the threshold. This test is more relevant for the household case to ensure that the sampling of households did not impact the density of observations on both sides of the threshold. Test by McCrary [2008] presented in Figure 6 shows that density of Euclidean distance does not jump discontinuously and is smooth at the threshold.

5.3 Triple Difference Estimation

In addition to RD methods an additional identification strategy is employed and provides robustness and generality to the results. The triple difference method is relevant here, as the regression discontinuity graphs show that, although there is a significant jump in outcome at the cutoff, the regression lines are relatively flat on both sides. As a secondary identification strategy a Triple Difference Approach is adopted. The triple difference approach utilizes village level panel data between year 2000 and 2008. Cell Phone Coverage was introduced into the rural areas between years 2000 and 2008. The panel data is only available for 398 villages in the study region as the data collected in year 2000 was sample based and did not have information on every village in the country. 2008 and 2000 datasets were matched manually and the details of this matching are provided in appendix. In addition comparable crop choice variables were generated to make the analysis possible. The details for the variable construction are also available in the appendix. The differencing approach is done across three dimensions: (a) between crops of different perishability within the sample village; (b) between villages with and without cell phone; (c) before and after cell phone coverage was introduced.

The equation for this identification strategy can be written as:

$$\begin{gathered}
\text{Crop}_{ijt} = \theta_0 + \theta_1 CellPhone_{jt} + \theta_2 HighlyPerishable \\
+ \theta_3 Post_t + \theta_4 (HighlyPerishable * CellPhone)_{ijt} \\
+ \theta_5 (HighlyPerishable * Post)_{it} + \theta_6 (Post * CellPhone)_{jt} \\
+ \theta_7 (Post * CellPhone * HighlyPerishable)_{ijt} + \\
\theta_8 + \xi_{ijt}
\end{gathered}$$

Here subscript i represents the crop, subscript j represents the village and subscript t represents the time period. The variable Highly Perishable is equal to 1 for extremely and highly perishable crops and 0 otherwise. The village level controls mentioned earlier are also included here in X.

6 Estimation and Results

6.1 Impact on Crop Choice

For the village level data, first a country wide analysis is conducted to look at the impact of cell phone access on probability of growing crops of different perishability. The country wide analysis uses information from all of the 52,378 villages in Pakistan. In the village level data it is not possible to differentiate extremely and highly perishable crops; therefore they are combined together. The results from the nationwide probit model in Table 3 show that access to cell phone coverage increases the probability of growing extremely and highly perishable crops by 0.29, statistically significant at 1% level. The probability of growing least perishable crops does not change significantly due to cell phone access. Although the coefficient has a positive sign, the economic and statistical significance indicates that the probability of growing least perishable crops does not change with cell phone coverage. It is important to understand that since these are binary variables it is difficult to establish any impact on the percentage of area under crops. The probit model is also repeated by trimming observations to villages in the province of Punjab. These results how that although the coefficient is slightly higher, but the results are consistent with the nationwide estimate.

Next, a triple difference identification strategy is adopted to study the impact of cell phone access on crop choice using the village level data. The results from this estimation are reported in Table 4. The results from the triple difference strategy utilizing data from 398 villages show that access to cell phone coverage increases the probability of growing extremely and highly perishable crops by 0.20, statistically significant at 1% level.

The FRD estimates of impact of cell phone access on probability of growing extremely and highly perishable crops lies in the range 0.23 to 0.26. The effect on probability of growing least perishable crops is statistically insignificant across all specification. The FRD results are robust to restricting sample to observations with in 5 km of the restriction line.

The household survey data is used for Sharp Regression Discontinuity (SRD) estimation. In this case using data on all 450 households the impact of cell phone access on area allocated to growing different crops is examined. SRD estimation results are reported in Table 6. SRD estimates show that the impact on area under extremely and highly perishable crops is positive and statistically significant. Estimated impact of cell phone access on percentage of area under extremely perishable crops lies in the range 24.5 to 27% while that on area under highly perishable crops is in the range 16 to 18%.[28] The village level results show that cell phone access has no statistically significant impact on probability of growing least perishable crops. The household data reveals that even though the probability remains unchanged the

[28] Data from household survey shows that while no one in the restricted zone owns a cell phone around 10 households in the non-deadzone do not own a cell phone. However they have a frequent access to cell phone from their neighbors.

percentage of area under level 3 and 4 crops goes down. The impact is negative and significant at 1% level.

6.2 Mechanisms

Next, an in depth analysis of the household survey is conducted to examine the different mechanisms through which cell phone access can impact crop choice. The first hypothesized mechanism is that, for the perishable crops, farmer and trader coordinate a sale date in advance, which leads to decrease in number of days between harvest and sale date and a reduction in post-harvest losses. This is referred to as the FTC effect. SRD results reported in Table 7 show that access to cell phone coverage leads to a decrease in number of days between date of harvest and date of sale of crops. For the extremely perishable crops the decline is of 5-7 days while for the highly perishable crops it is of 3-6 days. In contrast, the coefficient is insignificant in case of least perishable crops.

I hypothesize that an improvement in measure of farmer-trader coordination should lead to a reduction post-harvest losses. The SRD results for post-harvest losses are presented in Table 8. The post-harvest losses are reduced by 21 to 35% for the extremely perishable crops and 13 to 18% for the highly perishable crops. The impact of cell phone access on post-harvest losses of least perishable crops is positive but insignificant. This is consistent with the original story as the probability of matching harvest and sale date is also insignificant in case of these crops.

Another channel through which cell phone access can impact crop choice is that of improvements in information related to the accuracy of plantation dates, which as described earlier, is another source of information problem hindering production of perishable crops. The accuracy date is established in days by comparing farmers plantation dates to the local expert recommended period. The results for impact on the accuracy of plantation date are shown in Table 9. SRD results show that access to cell phone decreases the gap between actual date and the optimal period from 5-6 days for extremely perishable crops and 4-5 days for highly perishable crops. The accuracy of plantation dates for least perishable crops is not significantly impacted by access to cell phone coverage. This is due to the fact that only the yield of perishable crops gets impacted by the accuracy of plantation dates. In addition, the impact on crop yields is also considered. The results for crop yields are reported in Table 10. SRD results show that access to cell phone coverage increases harvest yield by 3-5% for level 1 crops and 3-4% for level 2 crops. The impact on yields of level 3 and 4 crops is positive but statistically insignificant. The SRD results point to the fact that access to cell phone coverage improves accuracy of plantation dates leading to higher yields for the perishable crops. It is important to consider that given the size of the coefficients this channel has much lower economic significance.

Finally, the impact of access to cell phone on prices received by farmers is also considered as plausible channel. The price received by farmers is compared to the market price and then taken as a percentage of market price. This measure of the percentage of the price lost would be set to 0 if the farmer received exactly same as the market price. This exercise is repeated for each crop and then estimate using household data and SRD. The results show that the access to cell phone coverage decreases the percentage of price lost for all the crops. The results as shown in Table 11 are statistically significant for all the crops. The magnitudes for all the crops are also similar and not significantly different from each other. This means that access to cell phone coverage reduces the percentage of the price lost, but does it uniformly for all the crops.

6.3 Income and Consumption

Finally I also examine the eventual impact on measures of well-being of the households. The well-being data is only available in the household survey. The results for measures of well-being are presented in Table 12. SRD Results suggest that access to cell phone coverage increases farmers household agricultural income by 10-15%. In terms of rupees this account to an additional Rs 1500 to 1800 per month or USD 14.29 to USD 17.15. In terms of comparison the household survey data suggests that the maximum cell phone usage expense incurred for agricultural purpose by no farmer exceeds Rs 300 or USD 2.86 in a month.

In addition the household survey also had a consumption module, which shows that the household consumption increased by 8-10%. These results suggest that the switching towards perishable crops due to ease in informational constraints is well-being enhancing for farmers in rural areas of Pakistan.

7 Robustness, Alternative Explanations and Falsification Tests

7.1 Location Decision and Mobility

One of the most important issues that pose threat to the identification strategy is the issue of farmers migrating and strategically locating to avoid living in the "Dead Zone". The relevant case in point here would be rural to rural migration for planting a different type of crop. In particular, this would require people to sell and then purchase a land in a different location. This type of transaction requires the existence of strong land markets. Marcel Fafchamps and Agnes R. Quisumbing (1998) Fafchamps & Quisimbing [1999], mention that land transactions are very infrequent in rural Pakistan.

In addition, analysis of the Pakistan Social and Living Standards Measurement Survey (PSLM) 2007-08 data to obtain information on volumes of land transactions was also conducted. As per the data there are total of 3684 households that cultivated land in the year prior to the survey. Out of these 41 households sold land, 83 households received land in gift or inheritance, 39 households purchased land and 69 households lost or gave it away. The land markets in Pakistan have been in this situation for a long time. Study of the Agricultural Census 2000 Data shows that the volume of land transactions and the percentage to have purchased a land is 2.9%. This volume also includes the purchases that made within the village as neither dataset allows measurement of the volume of transactions outside the village.

7.2 Information versus Communication

Cell phones provide a source of real time information and the ability of communicating with the market. In particular, this is different from other sources of information such as Radios, Television and Newspaper, which provide only a source of information. The Government has designed several programs for agriculture extension through Radio. This provides a basis for comparing the impact of radio versus cell phones on crop choices. It is the communication aspect of cell phones that enables access to real time information and also customized information. For example, farmers can access information from any market at any time. In addition, they can communicate with the market and mill owners.

The existence of sufficient variation in radio coverage provides the opportunity to perform the comparison. Radio is also the closest and most comparable source of information to cell phones. Smart phones have not reached the rural Pakistan as yet, hence, cell phones are restricted to voice and text feature. For obtaining information farmers use the cell phone's voice feature, as it only requires knowledge of numeracy, which is very high in Pakistan. Television requires viewing and can have other types of effects that make it less comparable to cell phone. In addition the cost of television is much greater than that of a cell phone. The cost of a radio is much more comparable to that of a cell phone.

Another very important factor regarding provision of cell phone as well as radio is that it is decided by permission of the Government of Pakistan. In particular Pakistan Telecommunication Authority licenses the cell phone tower placement and the Pakistan Broadcasting Company conduct a similar procedure for Radio. The cell phone variable is replaced with radio in the probit equation and the impact on probability growing extremely and highly as well as least perishable crops is estimated. Table 13 presents the results for this specification. First, the model for all 52,378 villages in the country is estimated. The results show that access to radio has no impact on probability of growing any category of crop. Although the coefficients are positive they are not statistically significant. Next the model is for the province of Punjab only. The results are still statistically insignificant, showing that radio access has no impact of crop choice.

7.3 Pre-Coverage Outcome Data Falsification Test

One method to conduct a falsification test is to replace the crop choice variable in 2008 with the crop choice variable from 2000 and see if cell phone coverage status today has any impact on crop choice in pre-coverage period. This is to say that before cell phone coverage was introduced, villages with and without coverage today did not have this differential across these villages which were later assigned to receiving cell phone coverage. The reason is that with the cross section it is not possible to show that for whatever reason this trend did not exist before coverage. For this test, the panel data of 398 villages in the study districts are considered. The results presented in Table 14 show that cell phone coverage status today has no statistically significant impact on outcome in year 2000 for either of the crops.

8 Policy Implications

The spread and availability of cell phones can be utilized to greatly benefit the agricultural households in rural areas of Pakistan. I show that farmers require information through the agriculture decision cycle as critical information such date of plantation, date of harvest and date of input application can have significant impacts on the farm output. ICTs provide a new tool, which can be leveraged to introduce different types of extension services for farmers.

Most agriculture related insurance products in developing countries mitigate the weather related risk in pre-harvest period. Under such conditions, coordination remains the only post-harvest risk mitigation strategy. My results suggest that although cell phones can enhance coordination, which can lead to farmers shifting towards producing cash crops, resulting in substantial income gains. Cell Phones have the ability to reduce but not completely mitigate the risk of producing cash crops. In order to encourage farmers to grow the highly perishable cash crops, there is a need to further mitigate farmers' risk in the post-harvest period. To give one example, despite several efforts and presence of substantially high returns, the flower cultivation has failed to grow in developing countries as it involves very high post-harvest risk due to very high rates of perishability for these crops. The plantation of such perishable cash crops can tremendously improve farmer household income in rural areas of developing countries if the post-harvest risks can be mitigated. More theoretical and empirical research is required to establish conditions under which post-harvest insurance products can be feasibly developed and implemented.

I also show that the impact of cell phone access on crop choice is heterogenous to the access to road network. My results show that although ICTs have the power to positively impact the farmer production choice, they not enough. In order to enhance the impact of ICTs on farmer production choices and income, these need to be combined with development of infrastructure such as roads.

9 Conclusion

Applying spatial regression discontinuity design methods to data from Pakistan, this is the first paper to shed light on the role of ICTs in enhancing farmer-trader coordination resulting in an increase in land allocated towards producing and successfully selling perishable cash crops.

In contrast to the earlier studies focusing on mechanisms related to price and weather related information, I show that the mechanism with the greatest economic significance is one of farmer-trader coordination. The decomposition of information channels suggests that the change in crop choice is predominantly driven by improvement in farmer-trader coordination. The impact of cell phone access on crop choice and farmer-trader coordination is the strongest for the extremely perishable crops and declines as I move down the perishability gradient. This further reinforces the significance of the hypothesized farmer-trader coordination mechanism. The magnitude and significance of the findings presented suggest that the importance of information in the agricultural sector of Pakistan can be compared to other important inputs such as seeds, credit and other machinery.

An important caveat to my findings is that although access to cell phone coverage improves the income and consumption of the agricultural households, it is still not possible to estimate the impact on the non-agricultural households living in rural areas as well as the spill overs ro urban population. Future work will try to address these questions by collecting additional data. A second additional aspect to be addressed by future research is to quantify the impact of farmer-trader coordination on traders stream of income. I am currently collecting data from micro-transaction records for the traders. The analysis of this data will analyze how improvement in farmer-trader coordination can impact the income and consumption of traders. Finally given the identification strategy outlined here can also be used for studying the impact of cell phone access on other sectors.

References

Agriculture Census Organization of Pakistan. (2008). Mouza Statistics of Pakistan.

Aker, J. (2010). Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *American Economic Journal: Applied Economics*, *2 (3)*, 45-69.

Aker, J., & Fafchamps, M. (2013). How does Mobile Phone Coverage Affect Farm-Gate Prices? Evidence from West Africa. *World Bank Economic Review*, *Forthcoming*.

Bayes, A. (2001). Infrastructure and Rural Development: Insights from a Grameen Bank Village Phone Initiative in Bangladesh. *Agricultural Economics*, *25(2-3)*, 261-272.

Chong, A., Galdo, V., & Torero, M. (2009). Access to Telephone Service and Household Income in Poor Rural Areas using a Quasi Natural Experiment for Peru. *Economica*, *74(304)*, 623-648.

Cole, S., & Fernando, N. (2012). *The Value of Advice: Evidence from Mobile Phone-Based Agricultural Extension.* Harvard Business School Working Paper 13-047.

Cole, S., Gine, X., Tobacman, J., Topalova, P., Townsend, R., & Vickery, J. (2013). Barriers to Household Risk Management: Evidence from India. *America Economic Journal: Applied Economics*, *5(1)*, 104-35.

Cole, S., Gine, X., & Vickery, J. (2014). *How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment.* Harvard Business School Working Paper 13-080.

Curtois, P., & Subervie, J. (2014). Farmer Bargaining Power and Market Information Services. *American Journal of Agricultural Economics*, *Published online: June 22, 2014*.

Deaton, A. (1992). Savings and Liquidity Constraints. *Econometrica*, *59(5)*, 1221-1248.

De Janvry, A., & Sadoulet, E. (2006). Progress in the Modelling of Rural Households' Behavior under Market Failures. In A. De Janvry & R. Kanbur (Eds.), *Poverty, Inequality and Development* (Vol. Essays in Honor of Erik Thorbecke).

Dell, M. (2010). The Persistent Effects of Perus Mining Mita. *Econometrica*, *78(6)*, 1863-1903.

Dercon, S. (1996). Risk, Crop Choice, and Savings: Evidence from Tanzania. *Economic Development and Cultural Change*, *44(3)*, 485-513.

Dercon, S., & Krishnan, P. (1996). Income Portfolios in Rural Ethiopia and Tanzania: Choices and Constraints. *Journal of Development Studies*, *32(6)*, 850-75.

Duke, J. A., & Ducellier, J. L. (1993). *Crc handbook of alternative cash crops.* CRC Press Inc. Retrieved from http://books.google.com/books/about/CRC$_{H}andbook_{o}f_{A}lternative_{C}ash_{C}rops.html?id = -tg7R4hU8hkC$

Fafchamps, M. (2003). *Rural Poverty, Risk and Development.* Elgar Publishing.

Fafchamps, M., & Minten, B. (2012). Impact of SMS-Based Agricultural Information on Indian Farmers. *World Bank Economic Review*, *28(1))*, 1-32.

Fafchamps, M., & Quisimbing, A. (1999). Human Capital, Productivity and Labor Allocation in Rural Pakistan. *Journal of Human Resources*, *34*, 369-406.

Food and Agriculture Organization. (2014). *The State of Food and Agriculture 2014: Innovations in Family Farming.* Food and Agriculture Organization.

Futch, M., & McIntosh, C. (2009). Tracking the Introduction of the Village Phone Product in Rwanda. *Information Technologies and International Development*, *5(3)*.

Gine, X., & Yang, D. (2009). Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi. *Journal of Development Economics*, *89(1)*, 1-11.

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

Grolleaud, M. (2002). *Post-Harvest Losses: Discovering the Full Story.* Food and Agriculture Organization.

Harris, J. R., & Todaro, M. P. (1970). Migration, Unemployment and Development: A Two-Sector Analysis. *American Economic Review*, *60(1)*, 126-148.

Imbens, G., & Lemieux, T. (2008). Regression Discontinuity Designs : A Guide to Practice. *Journal of Econometrics*, *142(2)*, 615-635.

International Food Policy Research Institute. (2013). *Global Food Policy Report.* IFPRI.

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.

Jensen, R. (2010). Information, Efficiency and Welfare in Agricultural Markets. *Agricultural Markets*, *41(S1)*, 203-216.

Kaminski, J., & Christiaensen, L. (2014). *Post-Harvest Loss in Sub-Saharan Africa: What do farmers say?* World Bank Policy Researh Working Paper no 6831.

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural Decisions After Relaxing Credit and Risk Constraints. *Quarterly Journal of Economics*, *129(2)*, 597-652.

Labonne, J., & Chase, R. (2009). *The Power of Information: The Impact of Mobile Phones on Farmers' Welfare in Philippines.* World Bank Working Paper 4996.

Macours, K. (2013). Volatility, Agricultural Risk, and Household Poverty: Micro-evidence from Randomized Control Trials. *Agricultural Economics*, *44*, Supplement 79-84.

McCrary, J. (2008). Testing for Manipulation of the Running Variable in the Regression Discontinuity Design. *Journal of Econometrics*, *142(2)*, 698-714.

Mitra, S., Mokherjee, D., Torero, M., & Visaria, S. (2013). *Asymmetric Information and Middleman Margins: An Experiment with West Bengal Potato Farmers.* Boston:Boston University.

Muto, M. (2009). The Impact of Mobile Phone Coverage Expansion on Market Participation: Panel Data Evidence from Uganda. *World Development*, *37 (12)*, 1887-1896.

National Research Council Board on Science and Technology for International Development. (1978). *Post-harvest Food Losses in Developing Countries.*

Oehmke, J. F. (1992). Technology, Impact and Agricultural Transformation: Lesson Learned from Impact Assessments. *USAID*.

Parker, C., Ramdas, K., & Savva, N. (2013). *Is IT Enough? Evidence from a Natural Experiment in Indias Agriculture Markets.* London Business School Unpublished.

Rosenzweig, M., & Binswanger, H. P. (1993). Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments. *Economic Journal*, *103(416)*, 56-78.

Singh, I., Squire, L., & Strauss, J. (1986). *Agricultural Household Models: Extensions, Applications and Policy.* Washington DC: World Bank.

Suri, T. (2011). Selection and Comparative Advantage in Technology Adoption. *Econometrica*, *79(1)*, 159-209.

Svensson, J., & Yanagizawa, D. (2009). Getting Prices Right: The Impact of the Market Information Service in Uganda. *Journal of the European Economic Association*, *7(2-3)*, 435-445.

Vargas Hill, R., & Ciceisza, A. (2012). An Experiment on the Impact of Weather Shocks and Insurance on Risky Investment. *Experimental Economics*, *15(2)*, 341-371.

Vargas Hill, R., & Torero, M. (2009). *Innovations in Insuring the Poor.* International Food Policy Reseatch Institute 2020 Focus 17 Brief 5.

Wellenius, B. (2002). *Closing the Gap in Access to Rural Telecommunications: Chile 19952002.* World Bank Discussion Paper 430.

World Bank. (2012). *World Development Report 2013.*

World Economic Forum. (2012). *Global Information Technology Report.*

Table 1: Summary Statistics from Village Level Data

Variables	10 km Band Restricted	10 km Band Not Restricted	10 km Band Difference of Means	5 km Band Restricted	5 km Band Not Restricted	5 km Band Difference of Means
Crops						
Extremely and Highly Perishable Crops (2008)	0.15	0.51	-0.36***	0.18	0.46	-0.28***
Extremely and Highly Perishable Crops (2000)	0.147	0.152	-0.005	0.151	0.153	-0.002
Infrastructure Availability						
Roads (2008) in 10s of Km	2.1	2.25	-0.15	2.1	2.25	-0.15
Roads (2000) in 10s of Km	3.3	3.6	-0.3	3.3	3.6	-0.3
Household Roof (Pucca)	0.68	0.72	-0.04	0.67	0.71	-0.04
Water Course Improvement Scheme	0.43	0.45	-0.02	0.44	-0.47	-0.03
Wheat Procurement Center	.023	.025	-0.0015	0.036	0.027	0.009
Retail Market	0.031	0.051	-0.02	0.042	0.053	-0.011
Health Center in Mouza	0.071	0.091	-0.02	0.069	0.083	-0.014
Landline phone	0.056	0.069	-0.013	0.061	0.073	-0.012
Primary School im Mouza boys	0.507	0.564	-0.057	0.541	0.582	-0.041
Primary School im Mouza girls	0.436	0.421	0.015	0.44	0.43	0.01
Sui Gas	0.031	0.044	-0.013	0.035	0.042	-0.007
Kerosene	0.023	0.025	-0.002	0.036	0.027	0.009
Wood	0.79	0.75	0.04	0.76	0.77	-0.01
coal	0.043	0.050	-0.007	0.046	0.055	-0.009
Animal Dung	0.833	0.821	0.012	0.89	0.819	0.071
Credit Facility Type						
ADBP	0.53	0.56	-0.03	0.57	0.59	-0.02
Coop Bank	0.65	0.67	-0.02	0.66	0.69	-0.03
Commercial Bank	0.262	0.31	-0.048	0.271	0.28	-0.009
Microfinance Bank	0.079	0.063	0.016	0.075	0.069	0.006
Government	0.138	0.154	-0.016	0.139	0.138	0.001
Broker	0.246	0.312	-0.066	0.289	0.334	-0.045
Sources of Employment & Opportunities						
Male Agriculture	0.89	0.91	-0.02	0.87	0.94	-0.07
Male Personal Business	0.25	0.31	-0.06	0.27	0.34	-0.07
Male Labour	0.627	0.591	0.036	0.671	0.572	0.099
Female Agriculture	0.354	0.379	-0.025	0.311	0.361	-0.05
Female Personal Business	0.023	0.027	-0.004	0.019	0.023	-0.004
Female Labour	0.357	0.412	-0.055	0.364	0.394	-0.03

$***p < 0.01, **p < 0.05, *p < 0.1$

The table shows village level summary statistics for both outcome and control variables for villages around the restriction. The first three columns present the data for villages with in 10 km of the restriction line, while the next three present data for villages with in 5 km of the restriction line. The restricted villages are the ones without cell phone access while the ones outside restriction have cell phone access. The results illustrate that villages with cell phone access have a higher probability of producing perishable crops. All infrastructure availability, credit facility and sources of employment and opportunities variables are balanced across the treatment and control villages.

Table 2: Summary Statistics from Household Level Data

Variables	Restricted Zone	Non-restricted Zone	Difference of Means
Number of Observations (Households)	225	225	
Crops			
Proportion of Area Extremely Perishable Crop (2013)	0.11	0.4	0.28***
Proportion of Area Highly Perishable Crop (2013)	0.13	0.32	0.19***
Proportion of Area Least Perishable Crop (2013)	0.76	0.28	-0.48***
Proportion of Area Extremely Perishable Crop (2003)	0.145	0.143	-0.002
Proportion of Area Highly Perishable Crop (2003)	0.138	0.129	-0.009
Proportion of Area Least Perishable Crop (2003)	0.717	0.728	0.011
Infrastructure			
Distance from Road in 10s of km	3.1	2.98	-0.12
Wealth Measure (Owning Assets)	0.56	0.58	0.02
Distance from Market in 10s of km	4.1	3.95	-0.15
Agriculture Credit	0.61	0.67	0.06
Other Variables (2013)			
Migration (Current)	0.057	0.067	0.01
Migration (Origin Different from Current location)	0.23	0.25	0.02
Education (Have access to someone who can read)	0.82	0.78	-0.04
Have a Non-Agricultural Income Source	0.289	0.287	-0.002
Land Cultivated in Acres	3.85	3.56	-0.29
Proportion of Land Irrigated	0.52	0.57	0.05
Last three generations in agriculture or not	0.95	0.969	0.019
No of Hours Working on Farm in H and P Season	9.86	10.05	0.19
Other Sources of Agriculture Information	0.07	0.059	-0.011
Agriculture Extension Service	0.03	0.025	-0.005

$***p < 0.01, **p < 0.05, *p < 0.1$

The table shows household level summary statistics and difference of means test for outcome and control variables for households around the restriction. The restriction area households are the ones without cell phone coverage while the ones in non-restriction area have cell phone coverage. The results illustrate that the percentage of area under perishable crops is not significantly different between two types of households in the pre-cell phone coverage period. Once cell phone coverage is introduced there is an increase in percentage of area under level 1 and 2 perishability crops for households lying in the non-restriction zone. All other covariates are balanced across the two types of households.

Table 3: Probit Results for Village Level Crop Choice

	(Probability of Being a Major Crop in the Village)			
	(Degree of Perishability of Crop)			
	(Highly & Extremely)	(Least)	(Highly & Extremely)	(Least)
Cellphone	0.29***	0.01	0.31***	0.04
	(0.004)	(0.02)	(0.002)	(0.1)
R-Square	0.38	0.25	0.29	0.17
Controls	Y	Y	Y	Y
District FE, Crop FE and District-Crop FE	Y	Y	Y	Y
Number of Observations	52,378	52,378	27,059	27,059

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents probit regressions from the village level national data and also for the case of all villages in the province of Punjab. Marginal effects are reported in the table. The regression includes full set of controls which are percentage of area cultivated, pre-coverage distance from pucca road network, wealth measures like roof structure of majority of households in the village, elevation, access to agricultural credit and access to irrigation. The regression also includes set of district specific, crop specific and district-crop specific fixed effects. Results show that there is an increase in probability of extremely and highly perishable crops while there is no effect on probability of growing lower and lest perishable crops both for the national level (column 1 and 2) case and the case of province of Punjab (column 3 and 4).

Table 4: Triple Difference Identification Strategy Results

	(1)
Cell Phone	0.05
	(0.28)
Perishability	0.03
	(0.04)
Cell Phone * Perishability	0.07
	(0.12)
Post	0.06**
	(0.031)
Post*Cellphone	0.03**
	(0.016)
Post *Perishability	0.11
	(0.50)
Post*Perishability*Cellphone	0.20***
	(0.05)
Number of Observations	398
R-Square	0.38

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for triple difference regression. This entails taking difference at three levels which include, (i)Perishable versus not; (ii) cell phone coverage versus no cell phone coverage and; (iii) before versus after. I report probit marginal effects. The data for this regression is for the 5 districts, where data is matched across the the mouza census 2008 which gives village level data and Agriculture Census 2000 which is household level with three staged stratified sampling. The matching between two datasets and aggregation is explained in appendix. The positive coefficient of triple interaction term shows that cell phone has positive effect on probability of growing perishable relative to less perishable.

Table 5: FRD Results for Village Level Crop Choice

	(Probability of Being a Major Crop in the Village)			
	(Degree of Perishability of Crop)			
	(Extremely & Highly)	(Least)	(Extremely & Highly)	(Least)
	(Quadratic in Distance from Restriction)			
Cell Phone	0.23***	0.032	0.26***	0.02
	(0.03)	(0.04)	(0.03)	(0.04)
	(Cubic in Distance from Restriction)			
Cell Phone	0.26***	0.012	0.245***	0.03
	(0.09)	(0.06)	(0.09)	(0.06)
	(Quartic in Distance from Restriction)			
Cell Phone	0.257***	0.035	0.24***	0.10
	(0.07)	(0.07)	(0.07)	(0.07)
	(Quadratic in Lat-Long)			
Cell Phone	0.24***	0.012	0.25***	0.09
	(0.02)	(0.09)	(0.03)	(0.07)
	(Cubic in Lat-Long)			
Cell Phone	0.23***	0.005	0.24***	0.08
	(0.09)	(0.07)	(0.08)	(0.09)
	(Quartic in Lat-Long)			
Cell Phone	0.267***	0.047	0.235***	0.09
	(0.08)	(0.10)	(0.09)	(0.45)
Controls	Y	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y	Y
Number of Observations	1785	1785	1094	1094
Size of Band Around Restriction	10km	10km	5km	5km

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for second stage of the fuzzy regression discontinuity applied to village level data. The results are presented for 10 km and 5km bands. I report results for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. Results indicate that access to cell phone coverage increases the probability of producing perishable crops while having no significant impact on the probability producing the least perishable crops. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.

Table 6: SRD Results for Household Level Crop Choice

	(Percentage of Household Area Under Crop)		
	(Degree of Perishability of Crop)		
	(Extremely)	(Highly)	(Least)
		(OLS)	
Cell Phone	0.28***	0.19***	-0.48***
	(0.08)	(0.06)	(0.18)
		(Quadratic in Distance from Restriction)	
Cell Phone	0.245***	0.16***	-0.41***
	(0.11)	(0.02)	(0.09)
		(Cubic in Distance from Restriction)	
Cell Phone	0.264***	0.165***	-0.42***
	(0.13)	(0.04)	(0.04)
		(Quartic in Distance from Restriction)	
Cell Phone	0.27***	0.18***	-0.45***
	(0.09)	(0.034)	(0.06)
		(Quadratic in Lat-Long)	
Cell Phone	0.265***	0.18***	-0.37***
	(0.08)	(0.03)	(0.06)
		(Cubic in Lat-Long)	
Cell Phone	0.244***	0.175***	-0.42***
	(0.10)	(0.04)	(0.08)
		(Quartic in Lat-Long)	
Cell Phone	0.271***	0.19***	-0.39***
	(0.06)	(0.05)	(0.07)
Controls	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y
Number of Observations	450	450	450

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for the sharp regression discontinuity applied to household level data. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. The extremely perishable crops are Tomatoes, Orange, Mangoes, Corn and Sugar Cane. The highly perishable crops are Onion, Garlic, Potatoes, Taro, Peas and Fresh Tumeric. The Least perishable crops are Millet, Feed, Sorghum, Rice, Wheat and Cotton. Results indicate that access to cell phone coverage increases the area allocated to producing extremely and highly perishable crops while decreasing the percentage of area allocated to growing the Least perishable crops. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.Weighting performed based on pweight in STATA. Weights constructed using the list of relevant households in the village.

Table 7: SRD Results for Impact on Number of Days Between Harvest and Sale Date

	(Number of Days Between Harvest and Sale Date)		
	(Degree of Perishability of Crop)		
	(Extremely)	(Highly)	(Least)
		(OLS)	
Cell Phone	-6.85***	-5.5***	0.75
	(0.07)	(0.04)	(0.60)
		(Quadratic in Distance from Restriction)	
Cell Phone	-6.13***	-5.34***	0.51
	(0.05)	(0.12)	(0.45)
		(Cubic in Distance from Restriction)	
Cell Phone	-5.85***	-5.15***	0.09
	(0.11)	(0.09)	(0.17)
		(Quartic in Distance from Restriction)	
Cell Phone	-6.83***	-5.45***	-1.11
	(0.75)	(0.95)	(0.99)
		(Quadratic in Lat-Long)	
Cell Phone	-6.96***	-6.15***	1.23
	(1.12)	(1.55)	(1.85)
		(Cubic in Lat-Long)	
Cell Phone	-5.50***	-4.89***	1.55
	(1.95)	(2.20)	(1.33)
		(Quartic in Lat-Long)	
Cell Phone	-4.87***	-3.39***	-1.21
	(1.75)	(1.13)	(0.97)
Controls	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y
Number of Observations	450	450	450

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for the sharp regression discontinuity applied to household level data for measuring impact of cell phone access on number of days between harvest and sale date. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. The extremely perishable crops are Tomatoes, Orange, Mangoes, Corn and Sugar Cane. The highly perishable crops are Onion, Garlic, Potatoes, Taro, Peas and Fresh Tumeric. The Least perishable crops are Millet, Feed, Sorghum, Rice, Wheat and Cotton. Results indicate that access to cell phone coverage decreases the number of days between harvest and sale for extremely and highly perishable crops, while having no impact on the least perishable. The decrease in number of days between harvest and sale is greatest for the extremely perishable. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.Weighting performed based on pweight in STATA. Weights constructed using the list of relevant households in the village.

Table 8: SRD Results for Impact on Post-Harvest Losses

	(Percentage of Crop Lost in Post-Harvest Losses)		
	(Degree of Perishability of Crop)		
	(Extremely)	(Highly)	(Least)
		(OLS)	
Cell Phone	-0.37***	-0.21***	-0.11
	(0.13)	(0.09)	(0.14))
		(Quadratic in Distance from Restriction)	
Cell Phone	-0.21***	-0.15***	0.04
	(0.09)	(0.07)	(0.11)
		(Cubic in Distance from Restriction)	
Cell Phone	-0.35***	-0.18***	0.07
	(0.04)	(0.09)	(0.05)
		(Quartic in Distance from Restriction)	
Cell Phone	-0.19***	-0.13***	-0.03*
	(0.03)	(0.05)	(0.019)
		(Quadratic in Lat-Long)	
Cell Phone	-0.25***	-0.13***	0.05
	(0.03)	(0.045)	(0.15)
		(Cubic in Lat-Long)	
Cell Phone	-0.34***	-0.195***	0.09
	(0.02)	(0.05)	(0.08)
		(Quartic in Lat-Long)	
Cell Phone	-0.23***	-0.15***	-0.06
	(0.11)	(0.04)	(0.059)
Controls	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y
Number of Observations	450	450	450

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for the sharp regression discontinuity applied to household level data for measuring impact of cell phone access on proportion of output lost to post-harvest losses. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. The extremely perishable crops are Tomatoes, Orange, Mangoes, Corn and Sugar Cane. The highly perishable crops are Onion, Garlic, Potatoes, Taro, Peas and Fresh Tumeric. The Least perishable crops are Millet, Feed, Sorghum, Rice, Wheat and Cotton. Results indicate that access to cell phone coverage decreases the proportion of output lost to post-harvest losses for extremely and highly perishable crops, while having no impact on the least perishable. The effect is strongest for the extremely perishable. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.Weighting performed based on pweight in STATA. Weights constructed using the list of relevant households in the village.

Table 9: SRD Results for Impact on Inaccuracy of Plantation Date

	(Inaccuracy of Plantation Date)		
	(Degree of Perishability of Crop)		
	(Extremely)	(Highly)	(Least)
		(OLS)	
Cell Phone	-8.5***	-4.9***	1.3
	(1.85)	(0.75)	(1.14)
		(Quadratic in Distance from Restriction)	
Cell Phone	-6.43***	-4.28***	-1.12
	(0.97)	(0.84)	(0.91)
		(Cubic in Distance from Restriction)	
Cell Phone	-5.38***	-5.21***	-0.98
	(0.86)	(0.75)	(0.82)
		(Quartic in Distance from Restriction)	
Cell Phone	-5.45***	-4.98***	-1.05
	(0.745)	(0.62)	(0.88)
		(Quadratic in Lat-Long)	
Cell Phone	-4.73***	-3.18***	-0.98
	(1.15)	(1.12)	(0.97)
		(Cubic in Lat-Long)	
Cell Phone	-5.47***	-4.21***	-1.15
	(0.87)	(1.20)	(1.13)
		(Quartic in Lat-Long)	
Cell Phone	-6.45***	-5.98***	-1.95
	(0.87)	(1.17)	(1.56)
Controls	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y
Number of Observations	450	450	450

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for the sharp regression discontinuity applied to household level data for measuring impact of cell phone access on inaccuracy of plantation date. The inaccuracy is measured by the difference between the farmer's plantation date and the optimal plantation date provided by the local agricultural experts. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. The extremely perishable crops are Tomatoes, Orange, Mangoes, Corn and Sugar Cane. The highly perishable crops are Onion, Garlic, Potatoes, Taro, Peas and Fresh Tumeric. The Least perishable crops are Millet, Feed, Sorghum, Rice, Wheat and Cotton. Results indicate that access to cell phone coverage decreases inaccuracy of plantation date for extremely and highly perishable crops, while having no impact on the least perishable. The effect is strongest for the extremely perishable. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.Weighting performed based on pweight in STATA. Weights constructed using the list of relevant households in the village.

Table 10: SRD Results for Impact on Crop Yield

	(Log of Crop Yield)		
	(Degree of Perishability of Crop)		
	(Extremely)	(Highly)	(Least)
		(OLS)	
Cell Phone	0.06***	0.03***	0.02
	(0.03)	(0.01)	(0.08)
		(Quadratic in Distance from Restriction)	
Cell Phone	0.05***	0.04***	0.01
	(0.01)	(0.009)	(0.02)
		(Cubic in Distance from Restriction)	
Cell Phone	0.049***	0.023***	0.005
	(0.02)	(0.008)	(0.03)
		(Quartic in Distance from Restriction)	
Cell Phone	0.037***	0.032***	0.003
	(0.009)	(0.001)	(0.004)
		(Quadratic in Lat-Long)	
Cell Phone	0.03***	0.02***	0.009
	(0.01)	(0.006)	(0.02)
		(Cubic in Lat-Long)	
Cell Phone	0.039***	0.027***	0.01
	(0.01)	(0.005)	(0.03)
		(Quartic in Lat-Long)	
Cell Phone	0.047***	0.035***	0.003
	(0.006)	(0.001)	(0.009)
Controls	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y
Number of Observations	450	450	450

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for the sharp regression discontinuity applied to household level data for measuring impact of cell phone access on log on crop yield. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. The extremely perishable crops are Tomatoes, Orange, Mangoes, Corn and Sugar Cane. The highly perishable crops are Onion, Garlic, Potatoes, Taro, Peas and Fresh Tumeric. The Least perishable crops are Millet, Feed, Sorghum, Rice, Wheat and Cotton. Results indicate that access to cell phone coverage increases the crop yield for extremely and highly perishable crops, while having no impact on the least perishable. The effect is strongest for the extremely perishable. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.Weighting performed based on pweight in STATA. Weights constructed using the list of relevant households in the village.

Table 11: SRD Results for Impact on Price Loss Relative to Market

	(Price Loss Relative to Market)		
	(Degree of Perishability of Crop)		
	(Extremely)	(Highly)	(Least)
Cell Phone	-0.34***	-0.38***	-0.29***
	(0.14)	(0.17)	(0.05)
	(Quadratic in Distance from Restriction)		
Cell Phone	-0.31***	-0.34***	-0.36***
	(0.15)	(0.16)	(0.09)
	(Cubic in Distance from Restriction)		
Cell Phone	-0.29***	-0.26***	-0.28***
	(0.11)	(0.08)	(0.12)
	(Quartic in Distance from Restriction)		
Cell Phone	-0.34***	-0.32***	-0.33***
	(0.15)	(0.13)	(0.14)
	(Quadratic in Lat-Long)		
Cell Phone	-0.29***	-0.35***	-0.26***
	(0.11)	(0.12)	(0.07)
	(Cubic in Lat-Long)		
Cell Phone	-0.34***	-0.25***	-0.27***
	(0.15)	(0.09)	(0.11)
	(Quartic in Lat-Long)		
Cell Phone	-0.37***	-0.31***	-0.32***
	(0.14)	(0.13)	(0.155)
Controls	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y
Number of Observations	450	450	450

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for the sharp regression discontinuity applied to household level data for measuring impact of cell phone access on price loss relative to market price. The variable is measured by taking difference of price farmer received and the market price and making a percentage of market price. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. The extremely perishable crops are Tomatoes, Orange, Mangoes, Corn and Sugar Cane. The highly perishable crops are Onion, Garlic, Potatoes, Taro, Peas and Fresh Tumeric. The Least perishable crops are Millet, Feed, Sorghum, Rice, Wheat and Cotton. Results indicate that access to cell phone coverage reduces the price loss relative to market for extremely, highly and least perishable crops. The effect is equally strong for all types of crops. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.Weighting performed based on pweight in STATA. Weights constructed using the list of relevant households in the village.

Table 12: SRD Results for Impact on Income and Consumption

	(1)	(2)
	(OLS)	
Cell Phone	0.17***	0.14***
	(0.05)	(0.04)
	(Quadratic in Distance from Restriction)	
Cell Phone	0.10***	0.08***
	(0.03)	(0.02)
	(Cubic in Distance from Restriction)	
Cell Phone	0.149***	0.069***
	(0.08)	(0.03)
	(Quartic in Distance from Restriction)	
Cell Phone	0.09***	0.096***
	(0.03)	(0.025)
	(Quadratic in Lat-Long)	
Cell Phone	0.13***	0.10***
	(0.05)	(0.03)
	(Cubic in Lat-Long)	
Cell Phone	0.157***	0.075***
	(0.04)	(0.01)
	(Quartic in Lat-Long)	
Cell Phone	0.087***	0.066***
	(0.02)	(0.03)
Controls	Y	Y
District, Crop and District-Crop FE	Y	Y
Number of Observations	450	450

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for the sharp regression discontinuity applied to household level data for measuring impact of cell phone access on agricultural income and consumption. The variable for the first column is the log of agricultural income and the variable for the second column is the log of households consumption. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.Weighting performed based on pweight in STATA. Weights constructed using the list of relevant households in the village.

Table 13: Probit Results for Impact of Radio Access on Village Level Crop Choice

	(Probability of Being a Major Crop in the Village)			
	(Degree of Perishability of Crop)			
	(Extremely & Highly)	(Least)	(Extremely & Highly)	(Least)
Radio	0.036 (0.226)	0.023 (0.212)	0.034 (0.242)	0.025 (0.016)
R-Square	0.24	0.18	0.21	0.14
Controls	Y	Y	Y	Y
District FE, Crop FE and District-Crop FE	Y	Y	Y	Y
Number of Observations	52,378	52,378	27,059	27,059

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents probit regressions from the village level national data and also for the case of all villages in the province of Punjab. Marginal effects are reported for the impact of radio network coverage on crop choice. The regression includes full set of controls which are percentage of area cultivated, pre-coverage distance from pucca road network, wealth measures like roof structure of majority of households in the village, elevation, access to agricultural credit and access to irrigation. The regression also includes set of district specific, crop specific and district-crop specific fixed effects. Results show that radio access has no impact on probability of producing the perishable as well as the least perishable ones.

Table 14: Placebo Test Looking at Impact of Cell Phone Access in 2008 on Crop Choice in 2000

	(Major Crop in the village in 2000)	
	(Degree of Perishability of Crop)	
	(Extremely & Highly)	(Least)
Cell Phone	0.01 (0.03)	0.007 (0.04)
R-Square	0.15	0.17
Controls	Y	Y
District FE, Crop FE and District-Crop FE	Y	Y
Number of Observations	398	398

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents for a pre-coverage outcome data placebo test. The outcome variable here is crop choice (probability of producing perishable crops) in year 2000, which is when cell phone coverage was not available. The insignificant coefficients indicate that before cell phone coverage was introduced villages with and without cell phone access were not significantly different in terms of the probability of producing perishable crops. The regression includes full set of controls which are percentage of area cultivated, pre-coverage distance from pucca road network, wealth measures like roof structure of majority of households in the village, elevation, access to agricultural credit and access to irrigation. The regression also includes set of district specific, crop specific and district-crop specific fixed effects.

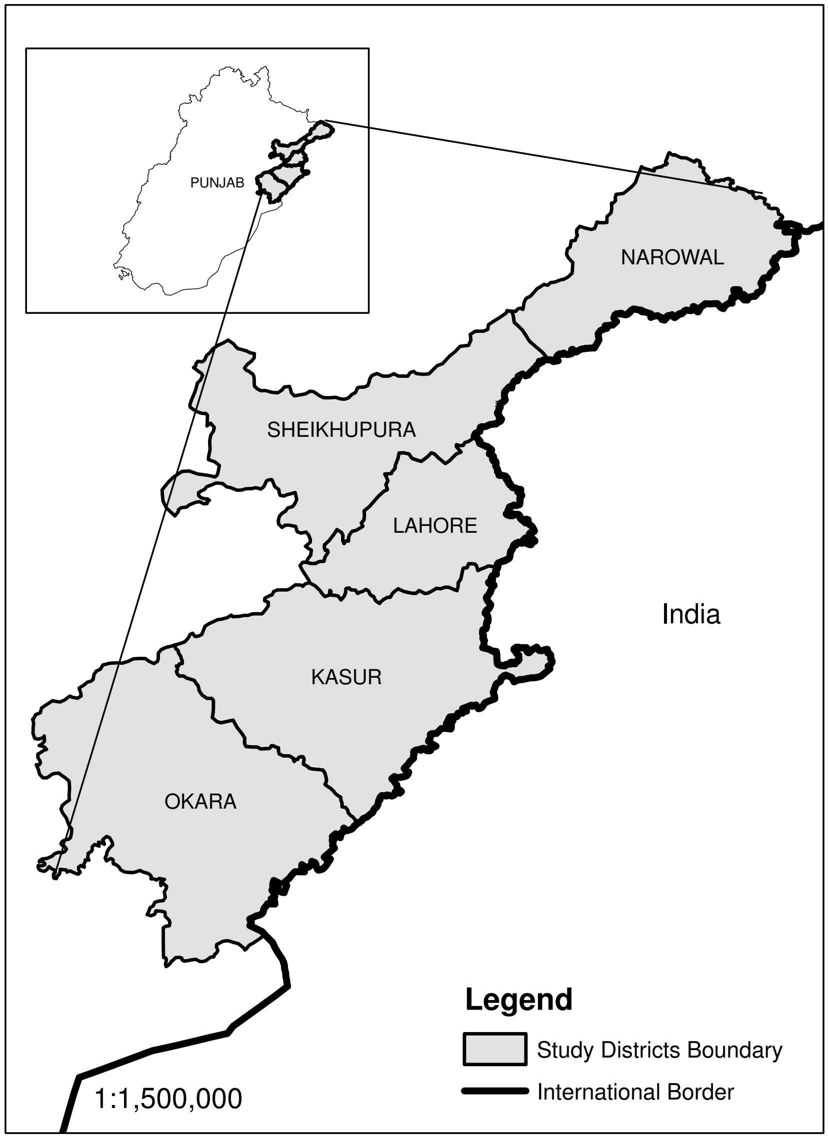

Figure 1: Map of the Study Districts

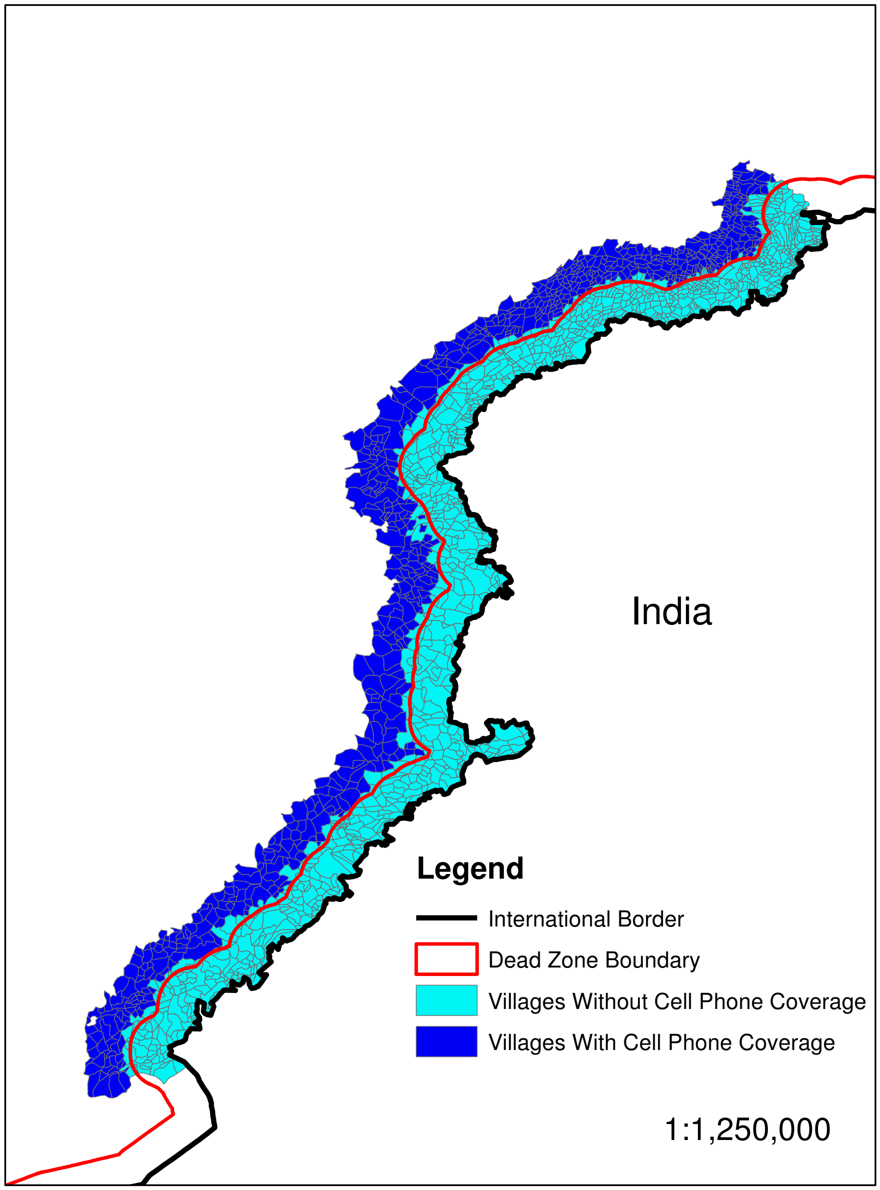

Figure 2: Map of the Restriction Coverage (Change in Color Shows Change in Coverage Status around the restriction)

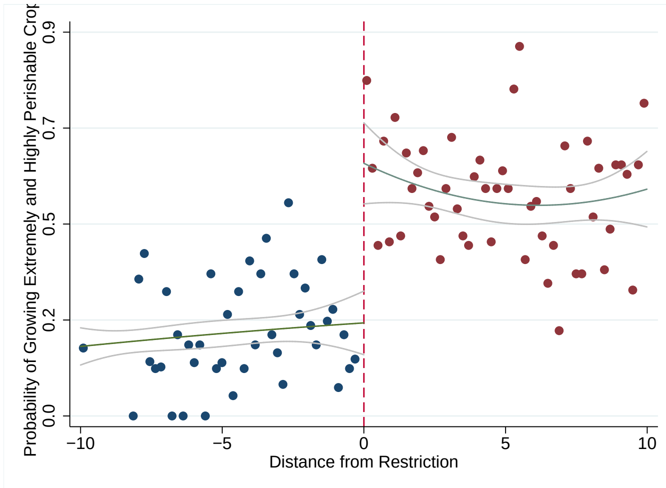

Figure 3: Discontinuity in Probability of Growing Extremely and Highly Perishable Crop with quadratic fit and 95% confidence intervals reported. The left hand side indicate villages without cell phone coverage and right hand side indicate villages with cell phone coverage. The graph shows that access to cell phone coverage increases the probability of producing extremely and highly perishable crops.

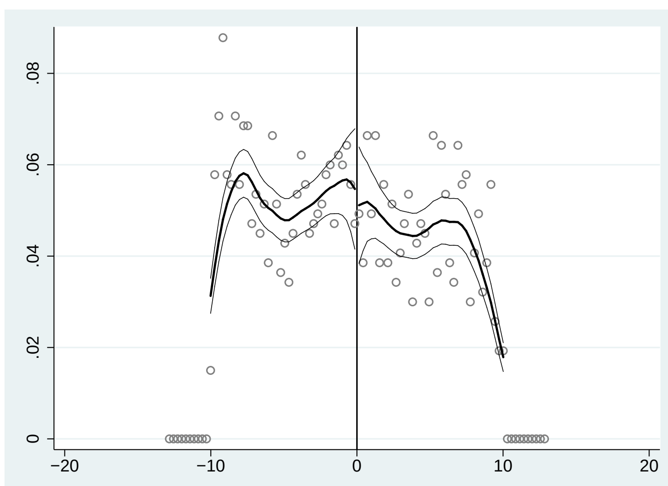

Figure 4: McCrary Density Test on Village Level Running Variable(Graph Generated using Stata Code McCrary (2008)). The graph indicates that density of villages is continuous at the cutoff.

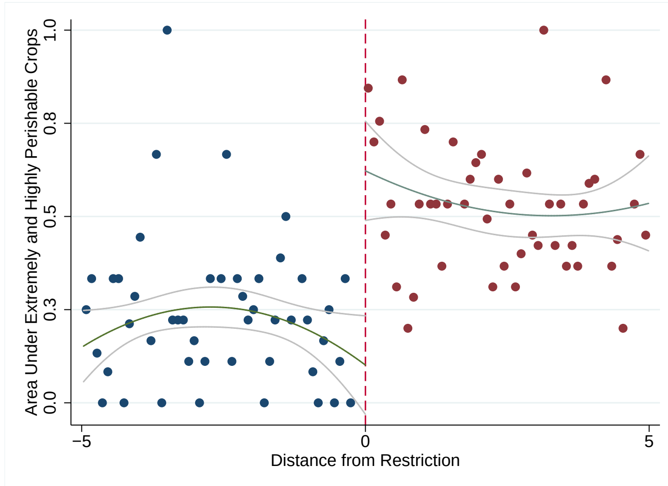

Figure 5: Discontinuity in Proportion of Area under Extremely and Highly Perishable Crop with Quadratic Fit and 95% confidence intervals. The left hand side indicate households without cell phone coverage and right hand side indicate households with cell phone coverage. The graph shows that access to cell phone coverage increases the area allocated to producing extremely and highly perishable crops.

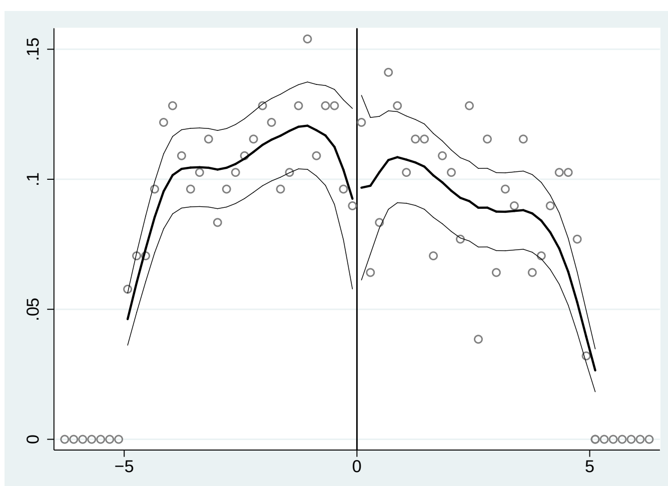

Figure 6: Figure shows the McCrary Density Test on Household Level Running Variable (Graph Generated using Stata Code McCrary (2008)). The graph indicates that density of sampled households is continuous at the cutoff.

Appendix A

Model

In this paper, I present a simplified model that provides framework for the mechanism through which cell phones can influence farmers production decision. Coordinating an advanced sale date with trader enables the farmer grow and successfully sell[29] their perishable cash crops and thus experience positive impact on their income.[30] The basis of this model is a simplified agricultural household model [Deaton, 1992, De Janvry & Sadoulet, 2006, Dercon, 1996]. The households decides the share of land allocated growing to different crops. Adapting from these earlier models, this paper explicitly models a specific type of risk: of not being able to sell crops in the post-harvest period and hence losing significant amounts to post-harvest losses.

Assumptions

The model makes the following assumptions for simplification:

(a) There are two crops in the system; One that is perishable and one that is not.

(b) Each farmer is endowed with total land which is normalized to 1. The farmer cultivates on all his land.

(c) The perishable crop provides the farmer with income Y_p , if sold immediately after harvest and otherwise nothing. This is called the *Extreme Perishability Assumption (EPA)*. The non-perishable crop always provides the farmer with income Y_{np}.

(d) The *Participation Constraint(PC)* holds: $Y_p > Y_{np} > 0$

(e) If farmer arrives at the market unannounced, all farmers participate in a lottery to sell their perishable crop. This is due to a periodic, random farmer-selection process that

[29] A successful sale here means to sell the crops before they perish.

[30] Although the focus of this paper model is on farmers, the traders also have an incentive to coordinate as they have limited storage capacity and with coordination they can purchase crops before they deteriorate, hence raising the quality of product that the trader receives. In addition this prevents the trader from having below capacity days, leading to higher income over season.

exists whenever there is excess supply in the market [Harris & Todaro, 1970]. I refer to this as the *Fair Trader Assumption(FTA).*

(f) Farmers can only visit the market in their own district.

(g) Farmer has constant relative risk aversion, which implies utility function of the form u(c)=c$^{\rho}$, where ρ <1 and c stands for consumption [Dercon, 1996].

Model Baseline Case: No Farmer Arriving at the Market Has Cell Phone

Due to FTA, the probability of the perishable being sold in the market is equal for every farmer who shows up on that day. Based on this, the ratio of trader capacity (normalized to 1) to total supply from farmer (θ) is the probability of making a sale, can be written as:$\frac{1}{\theta} = k$. The share of land devoted to the perishable in baseline case is given by σ_b.

The budget constraint is given by:

$$c = \sigma_b Y_p + (1 - \sigma_b) Y_{np}$$

The farmer chooses the proportion of land to devote to the perishable crop, σ_b so as to maximize his expected utility:

$$\max E(u(c)) = E[\sigma_b Y_p + (1 - \sigma_b) Y_{np}]^{\rho}$$

Optimizing with respect to σ_b , obtaining first order condition and solving reveals the expression of σ_b.

$$\sigma_b = \frac{Y_{np}}{Y_{np} + \frac{Y_p}{D-1}} \text{ where } D = [(\frac{k}{1-k})(\frac{Y_p - Y_{np}}{Y_{np}})]^{\frac{1}{1-\rho}}$$

Model Cell Phone Case: Some Farmers Arriving at the Market have Cell Phone

The farmers who have access to cell phones can now coordinate with the trader and hence their probability of making a sale when they arrive at the market goes to 1. Suppose that the proportion of farmers, who arrive with cell phones is some proportion $0 < \alpha < 1$ of the total supply *theta*. The new probability can be written as $k' = \frac{1-\alpha\theta}{\theta-\alpha\theta}$. Based on the assumptions that $\theta > 1$ and $\alpha < 1$, we can see that $k' < k$. This means that while coordination increases the probability of making a sale for those with cell phones, it reduces the probability of making a sale for those without cell phone.

In these conditions, for farmers with cell phones, $k = 1$. In this simplified model, it means that the risk of post-harvest losses has been entirely eliminated for farmers with cell phone. Based on PC holding, this means that the proportion of land allocated to growing perishable crops for farmers with cell phones will be 1 ($\sigma_c = 1$). Given the changed conditions, for farmers without cell phones and optimizing, proportion of land allocated to growing perishable crops can be written as:

$\sigma_{nc} = \frac{Y_{np}}{Y_{np}+\frac{Y_p}{D-1}}$ where $D = [(\frac{k'}{1-k'})(\frac{Y_p-Y_{np}}{Y_{np}})]^{\frac{1}{1-\rho}}$

Testable Results

Result 1: With coordination through cell phones, there is an increase in the share of land allocated to perishable crops for farmers with access to cell phone coverage

Proof: The proportion of land allocated to perishable crops in the baseline case when no one has cell phone coverage is:

$\sigma_b = \frac{Y_{np}}{Y_{np}+\frac{B}{D-1}}$

Based on earlier information, D is greater than 1. Therefore σ_b will be less than 1. The proportion of share allocated by farmer when they have cell phone access as shown in case

II is 1. This means that Hypothesis 1 holds.

Result 2: With coordination through cell phones, there is an decrease in the share of land allocated to perishable crops for farmers without access to cell phone coverage

Proof:

Earlier the model showed that k' is less than k. Also both k and k' are less than 1. Therefore the ratio of k to $1-k$ will be greater than the ratio of k' to $1-k'$. Therefore σ_b will be greater than σ_{nc}.

Welfare Implications:

Hypothesis 3: Access to cell phone coverage improves the welfare of farmers with cell phones while reducing the welfare of those without cell phone

Proof: The expected utility for all farmers when no cell phone exists can be written as:

$$E(U_c) = k[\sigma Y_p + (1-\sigma)Y_{np}]^\rho + (1-k)[(1-\sigma)Y_{np}]^\rho \tag{5}$$

The expected utility for farmers with cell phones when some farmers have cell phone coverage will be:

$$E(U_c) = (Y_p)^\rho$$

The expected utility for farmers out cell phones when some farmers arriving at the market have cell phone coverage will be:

$$E(U_c) = k'[\sigma_{nc}Y_p + (1-\sigma_{nc})Y_{np}]^\rho + (1-k')[(1-\sigma_{nc})Y_{np}]^\rho \tag{7}$$

Given that k is less than 1 and k' is less than k and taking result from hypothesis 2. It can be seen that relative to the baseline case cell phone access increases the welfare of farmers who get coverage and reduces the welfare of those who do not. The magnitude of relative increase to decrease depends on parameter values. The testing of this hypothesis is beyond the scope of this paper as data on consumption is not available overtime in either of the datasets. Future research following the farmers over time will reveal the relative magnitude of gain by cell phone farmers compared to the loss by farmers without cell phones.

Appendix B

Heterogeneous Treatment Effects

The impact of access to cell phone coverage can also vary depending on access to other types of infrastructure such as road networks. To study the heterogeneous effects I utilize village crop choice data.I also divide the sample into three parts with low, medium and high level of access to road network in the pre-cell phone coverage period. The access to road network is defined as high if there is a metalled road in 0-30 km of the village. Similarly it is defined as medium for 30-60 km and low for 60-90 km. I run FRD estimates using the village level data separately for each of the three level of road network access. The results presented in Table 14 show the impact on probability of growing extremely and highly perishable crops is highest for villages lying in the 0-30 km radius and lowest for 60-90 km. The coefficient for level and 1 and 2 crops however does remain positive and significant but decreases in magnitude as distance from metalled road increases.

The impact on probability of growing least perishable crops is insignificant for the low and medium distance. For the high distance from road network the probability of growing least perishable crops is positive and significant at 10% level of significance for two out of the three specifications. This suggests that in cases of remote villages where despite access to cell phone coverage the scarcity of road network does not allow perishable to become lucrative, the farmers grow more of level 3 and 4 crops.

Table 15: SRD Results for Heterogenous Impact on Crop Choice

	(1)	(2)	(3)	(4)	(5)	(6)
		(Quadratic in Distance from Restriction)				
Cell Phone	0.26***	0.18***	0.05***	0.05	0.07	0.09*
	(0.12)	(0.043)	(0.02)	(0.11)	(0.09)	(0.05)
		(Cubic in Distance from Restriction)				
Cell Phone	0.23***	0.164***	0.07***	0.06	0.03	0.085*
	(0.01)	(0.071)	(0.03)	(0.07)	(0.13)	(0.046)
		(Quartic in Distance from Restriction)				
Cell Phone	0.251***	0.175***	0.065***	0.02	0.04	0.076
	(0.11)	(0.06)	(0.03)	(0.13)	(0.15)	(0.08)
Controls	Y	Y	Y	Y	Y	Y
District,Crop and District-Crop FE	Y	Y	Y	Y	Y	Y

$***p < 0.01, **p < 0.05, *p < 0.1$

Regression 1 and 3 are for sample lying in range 0 to 30 km from road network. Regression 2 and 4 are for sample in range 30 to 60 km from road network. Finally regression 3 and 6 are for sample lying in the range 60 to 90 km. For column 1 , 2 and 3 outcome is binary variable is 1 if level 1 or 2 crop is grown and 0 otherwise. For column 4, 5 and 6 the outcome is binary variable is 1 if level 3 or 4 crop is grown and 0 otherwise. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.

Appendix C

Table 16: SRD Results for Fake Boundary Placebo Tests

	(1)	(2)	(3)	(4)	(5)	(6)
		(Quadratic in Distance from Restriction)				
Cell Phone	0.04	0.01	-0.01	0.05	0.03	0.001
	(0.15)	(0.05)	(0.07)	(0.14)	(0.07)	(0.02)
		(Cubic in Distance from Restriction)				
Cell Phone	0.02	0.04	0.05	-0.002	0.009	0.09
	(0.04)	(0.07)	(0.09)	(0.10)	(0.04)	(0.07)
		(Quartic in Distance from Restriction)				
Cell Phone	-0.02	0.07	0.073	0.01	-0.005	0.086
	(0.09)	(0.05)	(0.06)	(0.12)	(0.009)	(0.09)
Controls	Y	Y	Y	Y	Y	Y
District, Crop and District-Crop FE	Y	Y	Y	Y	Y	Y

$***p < 0.01, **p < 0.05, *p < 0.1$

Regression 1 and 2 are for sample using 5 km as the fake restriction boundary. Regression 3 and 4 are for sample using 15 km as the fake boundary. Finally regression 5 and 6 are for sample using 20 km as the fake restriction boundary. For column 1 , 3 and 5 outcome is binary variable is 1 if level 1 or 2 crop is grown and 0 otherwise. For column 2, 4 and 6 the outcome is binary variable is 1 if level 3 or 4 crop is grown and 0 otherwise. The results are presented for for quadratic, cubic and quartic polynomials in Euclidean distance from restriction. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.

Appendix D

Table 17: Results for First Stage of Fuzzy Regression Discontinuity

	(Cell Phone Coverage)
	(Quadratic in Distance from Restriction)
Lie in Deadzone	0.96***
	(0.03)
	(Cubic in Distance from Restriction)
Lie in Deadzone	0.94***
	(0.09)
	(Quartic in Distance from Restriction)
Lie in Deadzone	0.0.953***
	(0.07)
	(Quadratic in Lat-Long)
Lie in Deadzone	0.93***
	(0.02)
	(Cubic in Lat-Long)
Lie in Deadzone	0.94***
	(0.09)
	(Quartic in Lat-Long)
Lie in Deadzone	0.95***
	(0.08)
Controls	Y
District Dummies, Crop Dummies, Dist Crop Dummies	Y
Number of Observations	1785

$***p < 0.01, **p < 0.05, *p < 0.1$

Table presents results for first stage of the fuzzy regression discontinuity applied to village level data. I report results for quadratic, cubic and quartic polynomials in Euclidean distance from restriction as well as in longitude and latitude. Results indicate that lying in the deadzone increases the probability of having cell phone coverage. The regressions include full set of control variables as well as district specific, crop specific and district-crop specific fixed effects.

Appendix E

All data sources used in the analysis did not have a common code or direct identifier through which matching could be performed. Therefore I linked all datasets, using village name and their location in the administrative units. Section 1 outlines the linking procedure used to match Mouza Census 2008 to the GIS data and Section 2 outlines the procedure employed for matching Mouza Census 2008 to Agriculture Census 2000. All datasets utilized in the work have been graciously provided by the Agriculture Census Organization as well as the Population Census Organization. All these datasets are confidential and must be obtained from the relevant authorities for usage. The authority reserves the complete right to decide on data sharing procedures.

Part 1: Linking Mouza Census 2008 and GIS Data: This part details the procedure involved in the matching of Mouza Census 2008 dataset with the Mouza Boundary. As mentioned, no code or identifier exists between any two datasets. This appendix details procedure I applied to match the two datasets. In the absence of an actual identifier, the only way to perform the matching is over the village name. The Matching involves the use of local knowledge of nomenclature involved in naming of villages. Particularly in Pakistan the following problems create a challenge in performing this exercise: (a). Many villages have a common name or involve the use of numbers as identifiers e.g. Chak no1/8 etc. This also can many times result in errors made at data entry. This can cause additional difficulty in performing the matching. (b). The Mouza name present in dataset is often collected in Urdu and then changed to English by the data entry person. Therefore on several occasions the spelling in English in the data entered is based on the interpretation of the person entering the data. No standard conversion mechanism exists, therefore that can also lead to problems in performing matching. This is also due to the fact that no one to one link exists between any two alphabets in the two languages. Similarly accents are also different and hence people spell different words differently.

(c). Many times village is referred to as goth or killi or kalan or basti. In some datasets that prefix would be attached and in some it would not be. For example Goth X can also be listed as X. This is because Goth is village and some enumerators or data entry people may find the prefix irrelevant. Similarly someone may also list it as Mouza X. Therefore again care is needed when such decisions are made during the matching. In particular a detailed discussion with the relevant personnel is useful. (d). Villages shift with in administrative division particularly with in the union council. Consultation with local authorities is needed in such contexts. In addition on several occasions, when the local authorities fail to provide a satisfactory answer, which maybe due to several reasons, the importance of spatial data is helpful. For example in such a contexts, one can utilize the spatial data to see if the village shifts to a congruent union council then one can adjust accordingly.

Keeping the above problems mentioned in mind I conducted the matching for villages that lie in 5 districts of the 20 km of the India Pakistan Border only. In particular these 5 districts had not undergone any major divisions or documented changes.

1. First step was to match all villages that did not go through any change in administrative division. Villages were sorted in alphabetical; order and a village was considered matched if it had a same name and also it lied in the same union council and tehsil. Almost 95% of the matches were found using this method. Although numbers differ by districts. The exact numbers can be obtained from the datasets.

2. The next step was to match villages that shifted between union councils or became part of new union councils. For this step first it was considered whether the shift is to a contiguous union council. It was often the case that many villages from a union council formed a new union council. Hence that made it easily verifiable as several mouzas from the same union councils formed a new union council.

3. In addition an accuracy code was constructed and remains with data. A code of 1 is attached when a perfect match is found with village lying in the same union council. A code of 2 is attached when the village is found but in a different union council which is in

neighborhood of this union council. A code of 3 is attached when the match is never found. This was extremely rare. A code of 4 is attached when union council name is not available in one of the datasets. In that situation tehsil name is considered for matching.

Part 2: Linking Mouza Census 2008 and Agriculture Census 2000: The matching over the villages between Mouza Census and Agriculture Census has been performed for 4 districts of Punjab. The sample from these 4 districts had 400 villages total and a perfect match was found for 398 villages. These two sources of data were also matched over village name.

The next step was the generation of comparable variables across the two datasets. The Mouza Census 2008 has data on which of the 8 crops including wheat, sugarcane, cotton, vegetables, orchards, maize, rice and pulses are major crops of the mouza. Agriculture Census Organization collected this data by talking to a notable person in the village with sufficient triangulation. However no set percentage cut off has been defined. The Agriculture Census 2000 has household level data in a random sample of mouzas. In particular a three stage sampling strategy was adopted by the ACO. The relevant report can be consulted for details on the sampling procedure.

In the mouzas in Agriculture Census, I aggregated using crop area data for each household: 1. Area under wheat was generated from from dataset. 2. Area under sugarcane was generated from dataset. 3. Area under cotton was generated from dataset. 4. Area under vegetables was aggregated from area variables of each vegetable, tomatoes , rabi potatoes , onions , beetroot , peas , other rabbi vegetables , kharif potatoes , other kharif vegies. 5. Area under orchards was generated from if there was any orchard operated. It is important to note here that some of the fruits can be grown without having an orchard. However for the purpose of comparison I restrict the analysis to orchards growing fruits as the Mouza Census 2008 data only considers fruits grown in orchards. 6. Area under maize was generated from maize grown for human consumption and maize grown for use s animal feed. This was aggregated using variables for human consumption and for animal feed. This aggregation was done as the Mouza Census 2008 data uses total maize. 7. Area under rice was aggregated from are under basmati, irri and other types of rice. 8. Pulses area was aggregated from rabbi pulses, moong in kharif, mash moong in kharif, and all other pulses in kharif. After generating these household level variables, I aggregated them at village level. In particular analysis of the data shows that it is rare for only one or two people to grow a particular crop. In particular since this is a household sample, if anyone in the sample grows a crop, I assume that it will be a major crop. I generate a binary variable equal to 1 if the area under crop in that village is greater than 0.

Appendix E

.1 Decomposition of Mechanisms

As a next step this paper looks at the the impact of cell phone access on income from each crop. decompose the impact on farmers income by the three mechanisms that outlined mechanisms in the previous section.

$$M_{ij} = P_{ij} * Y_{ij} * (1 - \lambda_{ij}) \tag{8}$$

- subscript i denotes crop; - subscript j denotes farmer and can take a value of 0 or 1 depending on whether the farmer has cellphone coverage or not; - M denotes the income from crop i for farmer j;

The total impact or total effect (TE) of cell phone access on farmer income by crop can be expressed as:

$$TE_i = M_{i1} - M_{i0} \tag{9}$$

$$\implies [P_{i1} * Y_{i1} * (1 - \lambda_{i1})] - [P_{i0} * Y_{i0} * (1 - \lambda_{i0})] \tag{10}$$

These equations can be used for calculating the TE on each of the crop categories due to cell phone access. Utilizing the data I make calculations first to estimate the total effect of cell phone access on crop income. The results are reported for each the three crop categories in Figure 7.The results suggest that the impact of cell phone access is highest on the most perishable crops and declines as we move towards the less perishable crops.

Next a decomposition is conducted to try to isolate the impact of the three mechanisms which are the FTC, PIE as well as the WIE. To isolate the effect, it is assumed that only that variable changes and everything else remains constant. Therefore each of the three effects can be calculated in percentage terms. The decomposition for each of the effects can be conducted using equation below.

$$PIE_i = [[[P_{i1} * Y_{i0} * (1 - \lambda_{i0})] - [P_{i0} * Y_{i0} * (1 - \lambda_{i0})]]/[TE_i]] * 100 \tag{11}$$

$$\implies [[[P_{i1} - P_{i0}] * Y_{i0} * (1 - \lambda_{i0})]/[TE_i]] * 100 \tag{12}$$

$$WIE_i = [[[P_{i0} * Y_{i1} * (1 - \lambda_{i0})] - [P_{i0} * Y_{i0} * (1 - \lambda_{i0})]]/[TE_i]] * 100 \tag{13}$$

$$\implies [[[Y_{i1} - Y_{i0}] * P_{i0} * (1 - \lambda_{i0})]/[TE_i]] * 100 \tag{14}$$

$$FTC_i = [[[P_{i0} * Y_{i0} * (1 - \lambda_{i1})] - [P_{i0} * Y_{i0} * (1 - \lambda_{i0})]]/[TE_i]] * 100 \tag{15}$$

$$\implies [[Y_{i0} * P_{i0} * (\lambda_{i0} - \lambda_{i1})]/[TE_i]] * 100 \tag{16}$$

The results from the decomposition equations and the data from earlier estimations are presented in Figure 8. The results from the decomposition suggest that the FTC is heterogenous as it is the highest for the most perishable crops and declines as one moves across the perishability categories. The PIE and WIE are relatively uniform across all the categories. This suggests that in fact FTC is the only heterogenous income generating effect across the crop categories. Therefore based on this one can also conjecture that FTC is the most important factor driving the wedge between income changes for perishable and non-perishable crops.

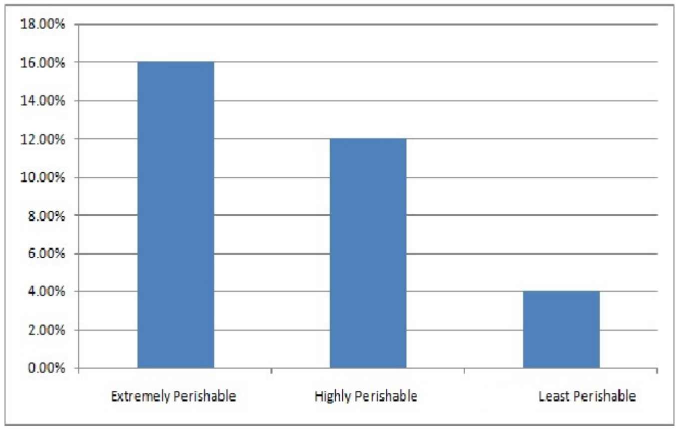

Figure 7: The graph presents the decomposition of impact of cell phone on agricultural income by crop. The results indicate that cell phone leads to the greatest change in income from extremely perishable crops, followed by the highly perishable one and then the least perishable.

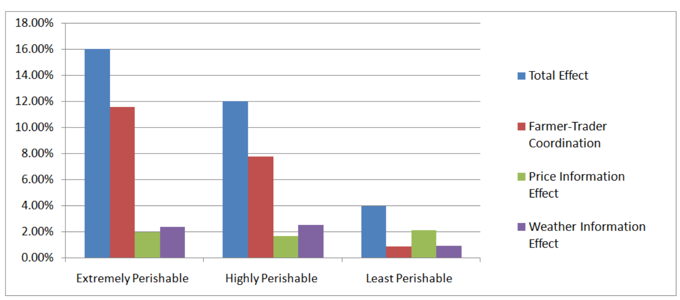

Figure 8: Graphs shows the breakdown of impact of cell phone access on agricultural income by crop and mechanism. The results show that for the extremely and highly perishable crops, FTC is the strongest mechanism in terms of change in income. In addition FTC is the only mechanism which has differential contribution to income as shown by the graph. The PIE and WIE have similar impacts on income from each crop.