Estimating Impact in Partial vs. General Equilibrium: A Cautionary Tale from a Natural Experiment in Uganda

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Preliminary.

August 2012

Abstract

This paper provides an example where sensible conclusions made in partial equilibrium are offset by general equilibrium effects. We study the impact of an intervention that distributed information on urban market prices of food crops through rural radio stations in Uganda. Using a differences-in-differences approach and a partial equilibrium assumption of unaffected urban market prices, the conclusion is the intervention lead to a substantial increase in average crop revenue for farmers with access to the radio broadcasts, due to higher farm-gate prices and a higher share of output sold to traders. This result is consistent with a simple model of the agricultural market, where a small-scale policy intervention affects the willingness to sell by reducing information frictions between farmers and rural-urban traders. However, as the radio broadcasts were received by millions of farmers, the intervention had an aggregate effect on urban market prices, thereby falsifying the partial equilibrium assumption and conclusion. Instead, and consistent with the model when the policy intervention is large-scale, market prices fell in response to the positive supply response by farmers with access to the broadcasts, while crop revenues for farmers without access decreased as they responded to the lower price level by decreasing market participation. When taking the general equilibrium effect on prices and farmers without access to the broadcasts into account, the conclusion is the intervention had no impact on average crop revenue, but large distributional consequences.

*Acknowledgement: We thank Frances Nsonzi and the management team at Foodnet for their assistance. We are grateful for comments and suggestions by Tessa Bold, Per Krusell, Daron Acemoglu, and seminar participants at Harvard Kennedy School, IIES, University of Frankfurt, and Centre d’Economie de la Sorbonne. Financial support from the Swedish International Development Agency, Department for Research Cooperation and Handelsbanken’s Research Foundations is gratefully acknowledged.

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1 Introduction

The bulk of empirical work using microdata, particularly in development economics, engages in partial equilibrium comparisons (Acemoglu, 2010). Although general equilibrium interactions can offset or even reverse sensible partial equilibrium conclusions (Heckman, Lochner, and Taber 1998), it also requires variation in exposure at the level of the economy; i.e. requires that the general equilibrium effects take place at the local level, to be credibly estimated using micro econometric approaches (Duflo, 2004). Thus most policy evaluation studies focus on impact in partial equilibrium.

In this paper, we assess the impact of providing price information in agricultural markets. This is an important question, as farmers’ lack of access to updated market prices, and the frictions that may entail, is a common explanation put forward to explain the low levels of market exchange in Sub-Saharan Africa (World Bank, 2007). As 75 percent of the world’s poor live in rural areas and make their livelihood mainly from farming crops, efforts to increase farmers’ willingness and return from engaging in market exchange is high on the policy agenda and ICT (Information and Communications Technologies) based interventions, where market prices are disseminated through radio, mobile, or internet, are now common in many parts of the developing world.

In this paper we use data from a policy experiment in Uganda aimed at increasing small-scale farmers willingness and return from engaging in market exchange by providing information on urban crop market prices. The Market Information Service (MIS) in Uganda, collected weekly data on market prices for a set of agricultural commodities in a subset of Uganda’s districts and disseminated the information to farmers through local FM radio stations. We contrast the estimated impact of the intervention under a partial equilibrium assumption and a general equilibrium assumption, which lead to very different conclusions. Under the assuming that the intervention was done on a small-scale and partial equilibrium analysis is suitable, the intervention had large and positive effects on farmers crop revenues. However, millions of farmers had access to the intervention, which led to general equilibrium effects on the price. When relaxing the assumption of fixed market price and allowing for behavioral responses among farmer without direct access to the intervention, the estimates imply negligible aggregate effects on crop revenue but large distributional consequences. We thus provide an example where sensible conclusions made in partial equilibrium are offset by general equilibrium effects.

To this end, we first present a simple general equilibrium model of the agricultural economy. In the model, asymmetric information gives rise to contracting frictions between farmers and traders, as rent-seeking traders operating in rural areas with low availability of updated price information

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1In Uganda, for example, only around 25 percent of output produced by small-scale farmer is sold and less than one-third (and for some crops as few as one-tenth) of the farmers participate actively in market exchange (as sellers), although sales of crops is the main (sole) source of cash income for many farmers.
have incentives to claim that prices in urban markets are lower than what they actually are. To
reduce these incentives, farmers cut down the amount they sell unless the trader reports a high
price. As a result, market exchange will be sub-optimally low. Providing farmers with access
to price information reduces these frictions, resulting in both increased market participation and
higher farm gate prices. In partial equilibrium, farmers that receive access to up-to-date market
price information ("informed farmers") are better off, while uninformed farmers are unaffected.
Allowing urban market prices to respond to the increased supply by informed farmers, however,
change the equilibrium outcomes. Uninformed farmers then faces lower market prices and respond
by reducing their market participation.

To assess the predictions of the model, we use variation in access to market price information
over time, across space, and between crops, and exploit the fact that market prices are set on local
(district) markets that are not (fully) integrated. We first show that market prices responded to the
MIS intervention, and the more so the higher the share of informed farmers. Specifically, a one
percent increase in number of informed farmers resulted in a 0.36 percent fall in district market
prices. We then exploit the household survey data to investigate the effects on individual level.
Under fairly weak identifying assumptions, we can estimate the difference in mean outcomes (in
general equilibrium) between informed and uninformed farmers. We find that access to market
information increased the likelihood of selling the crop by about 3 percentage points, or 13 \%,
in the informed group, while market participation among uninformed farmers fell by 6 percentage
points; that is a 9 percentage point difference in market participation between informed and un-
informed farmers as a result of the intervention. We find a similar effect for the total margin; i.e.
share sold, with informed farmers selling more (a 14\% increase) and uninformed farmers selling
less (24\% reduction). Informed farmers also benefitted from higher farm-gate prices. Ignoring the
general equilibrium effects, our result would suggest a large, positive, effect from the MIS inter-
vention, with crop revenue of informed farmers increasing by 75\%, albeit starting from a low level.
However, in general equilibrium, we estimate a much more modest increase in crop revenue for
the informed farmers (13\% increase), while uninformed farmers saw their crop income drop by an
estimated 35 \%. The aggregate impact of the intervention on average crop revenue was negligible,
but it had large distributional consequences: Consumers benefited from lower prices; informed
farmers benefited from higher farm revenues, while crop income fell for uninformed farmers.

The paper relates to a small and recent literature on the effects of improved access to market
information in the agricultural sector.\(^2\) Our work differs in important ways. First, the paper high-

\(^2\)Focusing on the ability to exploit arbitrage opportunities, Jensen (2007) evaluates the effects of the introduction
of mobile phones on market outcomes in the fishing industry in Kerala, India. He finds that by improving fishermen’s
and traders’ ability to communicate over large distances, the introduction of mobile phones improved arbitrage oppor-
tunities and resulted in reduced waste and decreased price dispersion across geographic markets. Studying traders’
search behavior in Niger, Aker (2008) finds similar effects on price dispersions across grain markets when mobile
lights the importance of assessing general equilibrium effects when analyzing policy interventions based on microdata, as stressed by Heckman, Lochner, and Taber (1998) and Acemoglu (2010). Second, as in Goyal (2010) we study the impact of increasing farmer access to price information, rather than traders access to information. Third, since farmers in Uganda almost exclusively sell their crops to traders at the farm-gate, we do not study the decision on where or to whom to sell the output. Instead, we investigate the impact on the economic exchange at the farm-gate conditional on the farmers’ access to information about the prevailing market price.

The remainder of this paper proceeds as follows: Section 2 discusses the institutional setup, including the Market Information Service project. The model is presented in section 3. Sections 4 and 5 discuss the data and the empirical strategy. The results are presented in section 5. Section 6 conducts robustness checks and Section 7 concludes.

2 Uganda’s Agricultural Sector

Uganda’s economy is predominantly agrarian. The agricultural sector employs roughly 80% of the labor force and is the main source of livelihood for more than 85% of the population. Almost 94% of the agricultural production take place on smallholder plots, including virtually all food production (Ministry of Finance, 2008). Detailed aggregate data for all crops is not available, but for maize, for example, it is estimated that 95% of the households engaged in maize production are small-scale farmers (with land holdings of 0.2-0.5ha), contributing over 75% of the marketable surplus of maize. Medium scale commercial farmers with 0.8-2.0ha of land under maize production contribute the remaining 25% (RATES Center, 2003).

Due to poor transportation infrastructure and lack of storage facilities, small-scale subsistence farmers sell off most of their surplus produce to rural traders immediately after harvest. For maize, rural traders, who operate in villages, constitute over 90% of the total number of maize traders and handle two-thirds of all traded maize. Typically, traders traverse villages on bicycles and pick-ups.
procuring produce at farm-gate prices on a cash basis. Moreover, almost no farmers engage in long-term contractual arrangements with a trader.\textsuperscript{5} Instead, most farmers engage with the market through traders on an informal manner, resulting in spot contracts between farmers and traders.

Traders either work independently or as agents of larger urban traders. Since they travel back-and-forth to the market, they are often well-informed, at least about the price in the district market where they are active (RATES Center, 2003).

Prices on most cash- and food crops vary greatly in district markets in Uganda over time. As an illustration, figure 1 depicts the weekly market price for cassava in the Kasese district market center (the coefficient of variation over time is 0.28, close to the mean of 0.24). Given these price variations, it is not surprising that farmers in Uganda view getting market information as one of their highest priorities (Ferris, 2004).

Prices also vary greatly across locations. Figure 2 plots the market price of beans during week 20 in 2001 across the participating MIS-districts. The variation in prices across districts at a given point in time suggests that to the extent that farmers sell their output to traders located in their own district, the market price in that district, rather than the average price in the country, is the key statistic. Figure 2 also suggests that the lack of adequate transportation infrastructure makes it difficult to exploit arbitrage across markets, thus implying that prices can be systematically different across space at a given point in time.

2.1 The Market Information Service

In 2000, the Market Information Service project was initiated by two agricultural research organizations (IITA and ASARECA) in association with the Ministry of Trade, Tourism and Industry in Uganda. The starting point of the project was survey data indicating that most farmers had limited knowledge of the current market prices in the main district market centers, and scarce information on price movements and market trends. By providing accurate, timely and appropriate information, the assumption was that small-scale farmers would be able to make better decisions about what to produce and where to sell their output. Timely and accurate information would also improve farmers’ bargaining position vis-à-vis local and regional traders.

In 2004, the Market Information Service was operating in 21 districts in Uganda.\textsuperscript{6} Figure 1 shows a map of participating districts. The project collected data, on a weekly basis, on market prices for 19 agricultural commodities. In practice, however, the MIS regularly reported prices

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\textsuperscript{5}In a survey on ten districts, Ferris et al. (2006) report that only 3\% of the farmers were trading on the basis of long-term contractual arrangements.

\textsuperscript{6}The total number of districts in 2004 was 56. Not all districts could be included in the MIS project because for budget and administrative reasons.
primarily on seven main food crops in Uganda (see details below): Beans, Cassava, Groundnuts, Maize, Millet and Sweet potatoes.

In each MIS district, price information was processed and disseminated through various radio stations. Price information was broadcast both weekly (a 15-minute radio program) and daily (a 2-4 minute news bulletin) in altogether eight local languages. The MIS targeted the most popular radio stations and in 2004, the MIS was estimated to reach seven of Uganda’s twenty-four million people each week (Ferris, 2004).\textsuperscript{7} The intervention, therefore, was on a large-scale.

3 A simple model of price information and agricultural market exchange

We model an economy consisting of a continuum of atomistic small-scale rural farmers, rural-urban traders, and consumers in an urban center. There is one good (crop) which is produced by the farmers, bought by traders at farmers’ farm-gates, and resold to consumers in the urban market center. The model consists of two parts. In the first part, we model how farm-gate prices and quantity are set, conditional on farmers’ access to information, and taking (urban) market prices as given. In the second part, we endogenize the market prices in the urban market center traders sell the crops bought from farmers. This then pins down the equilibrium quantities and prices both in the urban market center and at the farm-gates. The model will have two key features reflecting the conditions in many low-income countries, including Uganda as described above. First, since traders constantly travel back and forth between the urban market and the rural areas, the market price (and the demand shock) will be observable to traders. Rural farmers do not observe the market price, however. Second, competition between traders at the farm-gate is imperfect. This will then give rise to inefficiencies due to asymmetric information between traders and farmers.

3.1 The Farm-Gate Equilibrium

Let each farmer produce one crop of quantity $Q$, of which he can sell $q \leq Q$ to a trader and consume the rest, $c = Q - q$. We are interested in how much a farmer sells of what he produces and the prices he receives for his crops (henceforth "farm-gate price"), conditional on what information he has of the current retail market price (henceforth "market price"). The farmer’s payoff function

\textsuperscript{7}The MIS project initially bought air-time from the radio stations for the radio program. Interestingly, because of the popularity of the program among farmers, several commercial radio stations started to transmit the programs without public funds.
is

\[ U = R + u(Q - q), \]

where \( R \) is the total amount paid to the farmer (for \( q \)) and \( u(0) = 0, u'(c) > 0, u''(c) < 0, u'''(c) > 0. \)

Competition between traders at each farm-gate is imperfect.\(^8\) For simplicity, we assume that there is one trader at the farm-gate to whom the farmer can sell. The trader’s profit is

\[ \Pi = mq - R, \]

where \( m \) is the current market price in the urban retail market.\(^9\) We assume there are three possible market prices \( m_1 < m_2 < m_3 \), that are realized with probability \( \pi_1, \pi_2, \pi_3 \), respectively (and summing up to one).\(^10\)

The economy consists of a continuum of atomistic farmers, with measure one. The are two types of farmers: a share \( r \) informed (knows the realized retail market price) farmers and a share \( (1 - r) \) uninformed (cannot observe the realized retail market price) farmers, with \( r \in [0, 1] \).

In this set-up, the farmer is the principal that offers a take-it-or-leave contract to the trader on quantity \( q(m) \) and per-unit price \( p(m) \), or, analogously, revenue \( R(m) = p(m)q(m) \).\(^11\)

### 3.1.1 The uninformed farmer

The uninformed farmer cannot observe the market price but knows the distribution. This is essentially a standard bilateral contracting model, or monopolistic screening, under hidden information. The farmer suggests a contract conditional on the market price that the trader reports. The uninformed farmer’s problem is that the trader, who knows the market price, has incentives to claim that the market price is lower than it actually is. However, since the trader is more eager to buy when the market price is high, the farmer can possibly reduce the trader’s incentives to report a low market price by cutting down the amount he sells when the trader reports a low market price. By reducing the trader’s incentives to report a low market price, the farmer can reduce the informational

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\(^8\) Reasons for this could be high fixed costs (buying a truck) for becoming a trader, or collusion between traders. Fafchamps and Minten (2001) and Ferris (2004) provide evidence in favor of the assumption.

\(^9\) Transport costs \( t \) could easily be added, for example the linear cost \( tq \), for the trader without changing the main results.

\(^10\) Solving the farm-gate equilibrium with continuous prices does not change the main results. We choose discrete prices because it is more tractable.

\(^11\) An alternative set-up is to assume that the buyer (trader) offers the seller (farmer) a take-it-or-leave-it contract.
rent of the trader.

We are interested in the menu of contracts \( \{(q_j^U, m_j; j = 1, 2, 3) \} \) where superscript \( U \) denotes equilibrium outcomes when the farmers is uninformed. The optimal contract is defined by the following maximization program

\[
(3) \quad \max_{\{(q_j^U, R_j)\}} \sum_{j=1}^{3} \pi_j [R_j + u(Q - q_j)] \quad \text{subject to}
\]

\[
(4) \quad m_j q_j - R_j \geq 0 \quad \text{for all } j
\]

\[
(5) \quad m_j q_j - R_j \geq m_j q_k - R_k \quad \text{for all } j, k
\]

where (4) are the IR-constraints and (5) the incentive-compatibility (IC) constraints. Note that only one of the IR constraints binds since

\[
(6) \quad m_3 q_3 - R_3 \geq m_3 q_2 - R_2 \geq m_2 q_2 - R_2 \geq m_2 q_1 - R_1 \geq m_1 q_1 - R_1 \geq 0
\]

Note further that the Spence-Mirrless single-crossing condition holds, implying that the number of incentive constraints can be reduced to a smaller set of local downward incentive constraints and a monotonicity condition. The farmer’s problem can thus be stated as,\(^{12}\)

\[
(7) \quad \max_{\{(q_j^U, R_j)\}} \sum_{j=1}^{3} \pi_j [R_j + u(Q - q_j)] \quad \text{subject to}
\]

\[
(8) \quad m_1 q_1 - R_1 = 0
\]

\(^{12}\)The Spence-Mirrless single-crossing condition is

\[
\frac{\partial}{\partial m} \left[ -\frac{\partial U/\partial q}{\partial U/\partial R} \right] = \frac{\partial}{\partial m} \left[ -\frac{m}{-1} \right] > 0
\]

For details how to solve contract problems of this form see Bolton and Dewatripont (2005).
(9) \[ m_j q_j - R_j = m_{j-1} q_{j-1} - R_{j-1} \quad \text{for all } j > 1 \]

(10) \[ q_j \geq q_k \text{ if } m_j \geq m_k \]

To solve the constrained problem we set up the Lagrangian, assuming the monotonicity condition (10) holds. That is

\[ L = \max \sum_{j=1}^{3} \{ \pi_j [R_j + u(Q - q_j)] + \lambda_j [m_j q_j - m_{j-1} q_{j-1} - R_j + R_{j-1}] \} \]

\[ + \mu [m_1 q_1 - R_1] \]

where \( \lambda_i \) is the Lagrange multiplier associated with the IC-constraint at price \( m_i \), and \( \mu \) is the multiplier associated with the IR-constraint (8). Rewriting the first-order conditions yields the following conditions for \( q_j \),

(12) \[ -u'(Q - q_3^{UL}) + m_3 = 0 \]

(13) \[ -u'(Q - q_2^{UL}) + m_2 - \frac{\pi_3}{\pi_2} (m_3 - m_2) \leq 0 \]

(14) \[ -u'(Q - q_1^{UL}) + m_1 - \frac{\pi_2 + \pi_3}{\pi_1} (m_2 - m_1) \leq 0 . \]

The monotonicity condition (10) holds if assumption 1 holds, which we assume is the case.

(15) \[ \text{Assumption 1: } \frac{1}{\pi_1} (m_2 - m_1) \geq \frac{\pi_3}{\pi_2} (m_3 - m_2) \]

Three results are immediately apparent from (12)-(14). First, \( q_3^{UL} = Q - u_0^{-1}(m_3) \); i.e., the first-best quantity. This is the well-known "efficiency at the top" result. Second, \( q_1^{UL} \) and \( q_2^{UL} \) are lower than the first-best quantities where the size of the distortion, \( q_j^{FB} - q_j^{UL} \), is increasing in the potential size of the informational rent \( (m_{j+1} - m_j) \) for \( j = 1, 2 \). Third, the optimal solution might involve
no market exchange; i.e. \( q_j^U = 0 \). Specifically, given that assumption 2 holds, uninformed farmers do not sell at the lowest market price.

\[
(16) \quad \text{Assumption 2: } u'(Q) > \frac{1}{\pi_1} m_1 - \frac{1 - \pi_1}{\pi_1} m_2
\]

From the IR-constraints we can also determine the farm-gate prices, given by

\[
(17) \quad p_1^U = \{\text{no exchange}\}
\]
\[
(18) \quad p_2^U = m_2
\]
\[
(19) \quad p_3^U = m_3 - \frac{q_2^U}{q_3^U}(m_3 - m_2)
\]

### 3.1.2 The informed farmer

Now instead assume that the farmer knows the current market price. The constrained maximization problem is then

\[
(20) \quad \max \left\{ \sum_{j=1}^{3} \pi_j \left[ R_j + u(Q - q_j) \right] \right\} \quad \text{subject to}
\]
\[
(21) \quad m_j q_j - R_j \geq 0 \quad \text{for all } j,
\]

where (21) is the trader’s individual rationality constraints (IR).

Since the farmer has no incentives to relax the IR-constraints, we can solve for \( R_j \) from (21) and substitute into the maximimand (20). This yields an identical problem as that in the first-best. Thus, quantity sold under full information, \( q_j^I \), is equal to the first-best quantities

\[
(22) \quad q_j^I = Q - u_c^{-1}(m_j), \ j = 1, 2, 3
\]

From the IR-constraint we can solve for the farmer’s revenue, \( R_i \), and the unit price

\[
(23) \quad p_j^I \equiv \frac{R_j}{q_j} = m_j.
\]
3.2 The Urban Market Price

So far we have taken prices as given. In this section, we endogenize the market prices. Assume each trader sells all the crops that he has purchased from the farmers in an urban market center. Let the set of traders be large such that each trader is a price taker in the retail market at the urban center. Assume further that farmers vary in the minimum amount they are willing to buy from an individual farmer, such that a trade takes place provided that \( q^k_j \geq \eta \), where \( \eta \) is drawn from the uniform distribution \( U[0,1] \). As our focus is on the difference between informed and uninformed farmers, we assume \( q^I_2 > 1 > q^U_2 \), implying that the minimum amount to buy constraint only binds for (some) uninformed farmers at the market price \( m_2 \).

The supply is then a function of the market price and the fraction of informed farmers,

\[
S(m_j, r) = r \rho^I_j q^I_j + (1-r) \rho^U_j q^U_j, \quad j = 1, 2, 3
\]

where \( \rho^k_j \) is the probability that a farmer of type \( k = \{ I, U \} \) sells at price \( m_j \). Note that \( \rho^I_1 = 0 \), \( \rho^U_2 = q^U_2(m^*_2, m^*_3) \), and \( \rho^I_1 = q^I_1(m^*_1) \).

We can consider the demand coming from consumers consisting of urban non-agricultural households. For simplicity, we assume a linear demand function

\[
D(m_j, \epsilon_j) = d - \delta m_j + \epsilon_j, \quad j = 1, 2, 3
\]

where \( \epsilon_j \) is an aggregate demand shock. We assume there are three possible demand shocks \( \epsilon_1 < \epsilon_2 < \epsilon_3 \), that are realized with probability \( \pi_1, \pi_2, \pi_3 \), respectively (and summing up to one). We can think of the demand shock emanating from shocks in urban wages due to import or export price shocks for non-agricultural commodities. Key is that the demand shocks give rise to market price shocks that are unobservable to uninformed farmers but observable to traders and informed farmers.

The general equilibrium (the retail market equilibrium and the farm-gate equilibrium) is pinned by three market clearing conditions

\[
d - \delta m^*_1 + \epsilon_1 = r \rho^I_3 q^I_1(m^*_1)
\]
\begin{equation}
    d - \delta m_2^* + \epsilon_2 = rq_2^I(m_2^*) + (1 - r)\rho_2^U q_2^U(m_2^*, m_3^*)
\end{equation}

(28) 
\begin{equation}
    d - \delta m_3^* + \epsilon_3 = q_3^I(m_3^*)
\end{equation}

together with the farm gate equilibrium quantities implicitly defined by (12)-(13), and (22).

### 3.3 Predictions and intuitions

The model provides a set of testable predictions. We summarize the main ones below. Our focus is to estimate the effects of disseminating crop market prices, through the Market Information Services (MIS), on prices and market participation of small-scale farmers in partial and general equilibrium. The model highlights two mechanisms. First, the dissemination of information should reduce distortions and shift surplus from the buyer to the farmer and thereby increase market participation by farmers that can access the MIS. This is the main effect in partial equilibrium. Second, through the change in supply, dissemination of information will change both the mean and distribution of market prices. This is the general equilibrium effect.

Let \( x(m) \) be some outcome of interest (share sold for example) as a function of the vector of prices \( m = \{m_1, m_2, m_3\} \). Then the partial equilibrium average treatment estimate of the Market Information System is

\begin{equation}
    MIS_{PE} [x(m)] = E [x^I(m)] - E [x^U(m)]
\end{equation}

where \( x^I(m) \) [\( x^U(m) \)] represents the outcome for farmers that do [not] access the MIS, and \( PE \) denotes that the market price distribution \( (m) \) is assumed to be fixed. \( MIS_{PE} \) would be the relevant measure to use if the intervention was done on a small scale; i.e. when it is reasonable to assume that aggregate prices do not respond to the intervention. For a large scale policy experiment (like the Market Information Services), however, or when scaling up a pilot project, prices are likely to change. Thus, \( x^U(m) \) cannot be used as a counterfactual outcome. There are therefore two treatment effects, \( MIS_{GE}^I [x^I(m(r))] \) and \( MIS_{GE}^U [x^U(m(r))] \), for informed and uninformed farmers, respectively, where

\begin{equation}
    MIS_{GE}^I [x^I(m)] = E [x^I(m(r))] - E [x^U(m(0))]
\end{equation}
and

\[ MIS_{GE}^U \left[ x^U(m) \right] = E \left[ x^U(m(r)) \right] - E \left[ x^U(m(0)) \right] \]

and where the subscripts \( GE \) denotes that market prices are endogenously determined; i.e., these are the treatment effects in general equilibrium. In (30)-(31), \( E \left[ x^k(m(r)) \right] \) is the mean outcome for a farmer of type \( k = \{ I, U \} \) when a share \( r \) of farmers in the market access the MIS.

We are also interested in the average difference, denoted \( \Delta MIS_{GE}[x(m)] \), in outcomes between informed and uninformed farmers when a share \( r \) of the farmers access the MIS; i.e.

\[ \Delta MIS_{GE}[x(m)] = E \left[ x^I(m(r)) - x^U(m(r)) \right] \]

where \( \Delta MIS_{GE} = MIS_{GE}^I - MIS_{GE}^U \).

We focus on five outcome variables: (i) The probability that the farmer engages in market exchange (i.e., the extensive margin), \( \rho^U(m(r)) = 1 - \pi_1 + \pi_2 q^H_2(m(r)) \); (ii) The mean share sold, \( E[s(m(r))] = E[q(m(r))/Q] \); (iii) Farm-gate prices, \( p(m(r)) \); (iv) Crop revenues \( R(m(r)) = p(m(r))q(m(r)) \); and (v) Market prices, \( m(r) = \sum \pi_j m_j(r) \). We summarize the predictions for the main outcome variables below.

**Prediction 1.** Dissemination of information on market prices on a large scale results in a lower average market price and the more so the higher is the share of informed farmers; i.e. \( \partial E[m(r)]/\partial r < 0 \).

**Prediction 2.** Disseminating information on market prices results in increased market participation by those that can access information (informed farmers) and reduce market participation by those that cannot access information (uninformed farmers); i.e. \( MIS_{GE}^I[s(m)] > 0, MIS_{GE}^I[\rho(m)] > 0, MIS_{GE}^U[s(m)] < 0 \) and \( MIS_{GE}^U[\rho(m)] < 0 \). The effect on the average farm-gate price \( E[p(m)] \) is indeterminate, while crop revenues for informed farmers increase and crop revenues for uninformed farmer fall; i.e., \( MIS_{GE}^I[\pi(m)] > 0 \) and \( MIS_{GE}^U[\pi(m)] < 0 \).

The intuition behind these results are straightforward. By disseminating information on market prices, a share \( r \) of farmers become informed. Informed farmers do not have to sacrifice allocative efficiency, or give up informational rents, to incentivize traders and therefore sell a larger share of their output. As a consequence, the aggregate supply curve shifts outward and the more so the higher is \( r \). This shift in supply shifts the market price distribution and leads to a lower average market price. As a result, uninformed farmers face on average lower farm-gate prices and therefore reduce the amount they sell. Moreover, as prices fall, a higher share of uninformed farmers will
hit the minimum amount to sell constraint, thus also having an impact on the extensive margin. $MIS^L_{GE} [p(m)]$ and $MIS^U_{GE} [p(m)]$ are indeterminate. This is driven by the fact that becoming informed has two effects on the farm-gate price: a direct incentive effect (positive) and an indirect selection effect (negative). The incentive effect is positive since, conditional on a market price, the informed farmer does not have to give up informational rents to incentivize the trader. The selection effect, however, is negative since the informed farmer is willing to sell at (low) prices where uninformed farmers are not, leading to a lower average farm-gate price.

4 Data

To test the predictions of the model, we want to measure whether a farmer is informed about the market price, whether he engages in market exchange ($\rho_i$), the share of output sold ($s_i$), the farm-gate price per unit sold ($p_i$), crop revenues ($\pi_i$), and market prices ($m_i$). We are interested in whether the Uganda Market Information Service that informed farmers about prevailing market prices through local radio stations affected the outcome variables as predicted by the model.

We use three data sets: The Uganda National Household Survey 1999/2000 and 2004/2005 (hereafter UNHS 1999 and UNHS 2005) and data from the Market Information Service, provided by Foodnet. The two household surveys include a full crop module, enabling us to calculate farm-gate prices for crops sold, $p_i$ in the model, as well as measures of market participation on both the extensive ($\rho$) and intensive ($s$) margins. The farmer data is measured at the plot level. Summary statistics of the UNHS 1999 and 2005 are reported in table 1. The data from the Market Information Service contains weekly data on collected urban market prices (from 2000 to 2005, with some missing data). There is one urban market per district. The broadcasts were phased in, starting in 2000 for the earliest district (Kampala) and completed by 2004.\(^{13}\) Using the UNHS 1999 dataset, we are able to use data from before the broadcast started. By using the UNHS 2005 dataset, we can use data for when the MIS was fully operational. In addition, for a subset of eight districts, we have been able to collect information on the exact month in which broadcasts started.

4.1 Outcomes ($\rho, s, p, m$)

In our sample of the UNHS 1999 and 2005 datasets, there are 7960 and 5733 farmers, respectively. Each farmer in the dataset produces one crop or more. We use crop level data which contains information on what type of crop that is produced, the quantity produced, the quantity sold, and

\(^{13}\)We drop the capital Kampala from our sample since there are no rural farmers in Kampala.
the price for the quantity sold. We also have access to a subset of the MIS radio scripts that were used for the broadcasts. They show that there were some minor crops for which price information was collected but very seldom broadcast. We use the main MIS crops, defined as those that were reported in radio scripts on average at least once per month in 2004 and for which we have at least 1,000 data points (farmer plots) in the 2005 UNHS survey.\textsuperscript{14} The main MIS crops constitute 76\% of the reported MIS crop observations in the crop surveys.

We take a conservative approach with respect to outliers, all of which clearly seem to be a result of misreporting. Thus, we drop all price observations with a reported unit price (the survey contains information on the quantity produced of each crop, the quantity sold, and the total value of the sale) higher than the highest reported weekly market price across all MIS district market centers and we drop all price observations with a unit price below roughly 0.01US$ (which corresponds to dropping all observations below the 1th percentile of the distribution for each crop). We also drop observations with a higher quantity sold than harvested.

We use a similar rule to define control crops (non-MIS crops). Specifically the control crops are those crops for which the MIS did not collect data for and that constitute at least one percent of the reported non-MIS crops in the 2005 UNHS survey. We drop coffee since the Uganda Coffee Development Authority (UCDA) runs a similar radio program for coffee in the main coffee producing areas of Uganda.

For each crop, we construct an indicator variable equal to one if any of the output was sold, and zero otherwise, as well as the share of the output that was sold.\textsuperscript{15} For farm-gate prices, we then calculate the per kilogram price by dividing the total price by the quantity sold (in kilograms).\textsuperscript{16} We can then calculate the standardized farm-gate price.\textsuperscript{17}

The UNHS 1999 and 2005 datasets also have information on whether the farmer owns a radio, whether the farmer sold directly to the district market center and a quiz testing the farmer’s knowledge of agricultural technology. The latter variable consists of seven multiple answer questions.\textsuperscript{18} We construct a variable measuring the fraction of correct answers by the farmer.

\textsuperscript{14}1,000 plots correspond to roughly 1\% of the reported MIS crops. We also exclude Bananas/Matooke since the MIS only reported one type of Banana/Matooke price while the crop modules list three types of plantain banana crops (Matooke) and we were unable to separate for which one there were broadcasts.

\textsuperscript{15}In Uganda, there are two growing seasons per year. For each UNHS dataset, the crop data contains information for each season.

\textsuperscript{16}The datasets also contain information on type of buyer. In 2005, 70\% of the output were sold to a private trader in the household’s village, 16\% directly to another consumer or neighbor/relative, 9\% at the district’s market center, and 5\% to “other type of buyers”. For simplicity, although the output is not always literally sold to a private trader at the farm-gate, we label the price of all transaction types as the “farm-gate price”.

\textsuperscript{17}That is, $p_{ij} = (\tilde{p}_{ij} - \bar{p}_j)/\sigma_j$, where $\tilde{p}_{ij}$ is the farm-gate price/kilogram in Uganda Shillings received for the sold quantity of crop $j$ by household $i$; $\bar{p}_j$ is the mean farm-gate price in the sample, and $\sigma_j$ is the corresponding standard deviation.

\textsuperscript{18}Such as: Which of the following cassava planting methods provides better yields? 1. Vertically planted sticks; 2. Horizontally planted sticks; 3. Both; 4. Don’t know.
For urban market prices, we use the MIS data provided by Foodnet. By exploiting the data for the subset of eight districts where we know the month in which the broadcasts started, we can divide the ten districts into early and late MIS districts. The early districts received broadcasts starting in February 2001 and the late districts received broadcasts starting in September 2002.\(^{19}\)

\section{Empirical Strategy}

This section outlines how we estimate the predictions of the model. We first present the coefficient of interest and the empirical challenges of estimating it. We then present our empirical strategy and specifications for how we estimate the effects.

\subsection{Prediction 1: Market Price}

Prediction 1 implies that when the share of informed farmers increases, the prices in the urban retail market should decrease due to increased supply. To test this prediction, we use the market price data from the urban markets and estimate the following main specification\(^{20}\)

\begin{equation}
\log(m)_{cdt} = \beta_1(idist_d \times post)_{dt} + \gamma_t + \mu_{cd} + \epsilon_{cdt},
\end{equation}

where \(m_{cdt}\) is the price of crop \(t\) in the main urban market of district \(d\), in week \(t\). The variable \(idist_d\) is a dummy variable indicating if the district received broadcasts starting in February 2002, and zero if the district did not receive broadcasts until after the sample period. \(post_{dt}\) is a dummy variable indicating post-February 2002, and zero if it is pre-February 2002. Since the broadcasts increased the number of informed farmers, by prediction 1 we expect \(\beta < 0\).

\begin{equation}
\log(m)_{cdt} = \beta_1(idist \times post)_{cdt} + \beta_2(post \times \bar{r})_{cdt} + \beta_3(idist \times post \times \bar{r})_{cdt} + \eta_t + \mu_{cd} + \epsilon_{cdt}
\end{equation}

where \(\bar{r}\) is the percentage of farmers in the district with radio.

\(^{19}\)The early districts are Jinja, Kabale, Masindi, Mbarara, and Soroti. The late districts are Gulu, Mbale, and Tororo.

\(^{20}\)The urban market price data contains data both on off-lorry prices and retail prices. We use the off-lorry prices as these are what is paid to the traders. The two prices are naturally very similar: the correlation is 0.96.
Identifying assumptions: In equation (33), the diff-in-diff assumption is that in the absence of price information broadcasts, early and late MIS districts would have parallel trends in market prices. Similarly, in equation (34), we assume that radio farmers listen to the radio and are informed, while farmers without radio are uninformed. Most importantly, we assume that in the absence of broadcasts, the market price in districts with larger fraction of farmers with radio would have parallel trends with districts with a smaller fraction of farmers with radio.

Under these assumptions, by prediction 1 we expect \( \beta^3 = \beta^m < 0 \).21 It is worth noting that if some farmers with radio are uninformed (e.g. because they do not listen to the radio), or if farmers without radio are informed anyways (e.g. by talking to informed farmers with radio), then we will underestimate the true effects. In this case, the estimated \( \beta^4 \) and \( \beta^5 \) can be interpreted as lower bounds of \( \beta^3 < \beta^m \). To assess this assumption, we run a set of placebo regressions using samples

5.2 Prediction 2: Farm-Gate Outcomes

To test prediction 2, we exploit variation across time (before and after broadcasts begin), radio ownership (of the farmer), crops (i.e. included or not included in the broadcasts), and districts (participating in the MIS program). By exploiting variation across crops we are able to use farmer fixed effects, which will be our most restrictive specification. We estimate two triple differences (DDD) specifications.

5.2.1 DDD over time

The first DDD specification is:

\[
y_{icdt} = \beta^1 r_{icdt} + \beta^2 (r \times post)_{icdt} + \beta^3 (r \times ic)_{icdt} + \beta^4 (ic \times post)_{icdt} + \beta^5 (ic \times post \times r)_{icdt} + \eta_t + \mu_{cd} + \epsilon_{icdt}.
\]

where \( y_{icdt} \) is the outcome of farmer \( i \) in district \( d \) producing crop \( c \) at time \( t \). The variable \( r_{icdt} \) is a dummy variable equal to one if the farmer owns a radio, \( post \) is a dummy variable equal to one if the observation is after the broadcasts started (i.e. the 2005 UNHS survey), and zero if it is from before (UNHS 1999). \( ic \) is a dummy equal to one if the farmer’s crop is included in the set of broadcasted crops. We use year fixed effects and district-by-crop fixed effects \( \mu_{cd} \). Our key outcome variables are: \( \ln(s_{icdt}) \), the log of the share of output sold (i.e. the total margin)\(^{22}\); \( \rho_{icdt} \).

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21 Notice the slight abuse of the notation, since we are using logged outcome variables for the total margin and revenue in the regression, while in the model they are in levels.

22 To deal with undefined log function at zero, we add 1 kilogram to the true amount sold.
an indicator variable equal to one if the farmer sold any of his crop \( c \) output (i.e. the extensive margin); \( p_{icdt} \), the standardized farm-gate price per kilogram received for crop \( c \) by farmer \( i \), and; 
\( R_{icdt} \) is the crop \( c \) revenue of farmer \( i \). The main regressions use data from MIS districts only. We cluster the standard errors at the district-crop level.

**Identifying assumption in equation (35):** Farmers with radio are informed and farmers without radio are uninformed. Farmer selection into radio ownership may be different depending on the crop grown, but this selection is constant over time.

Under these assumptions, by predictions 2 we will use OLS to consistently estimate:

- **Extensive Margin:** \( \beta^5 = \beta^\rho > 0 \) and \( \beta^4 = \gamma^\rho < 0 \).
- **Total Margin:** \( \beta^5 = \beta^s > 0 \) and \( \beta^4 = \gamma^s < 0 \).
- **Farm-Gate Price:** \( \beta^5 = \beta^p \leq 0 \) and \( \beta^4 = \gamma^p \leq 0 \).
- **Revenue:** \( \beta^5 = \beta^R > 0 \) and \( \beta^4 = \gamma^R < 0 \).

It is worth noting that if farmers with radio are sometimes uninformed (e.g. because they do not listen to the radio at times), or if farmers without radio are informed anyways (e.g. by talking to informed farmers with radio), then we will underestimate the true effects. In this case, the estimated \( \beta^4 \) and \( \beta^5 \) can be interpreted as lower bounds of \( \beta^\rho, \gamma^\rho, \beta^s, \gamma^s, \beta^p, \gamma^p, \beta^R, \) and \( \gamma^R \). Furthermore, we will assess the critical second identification assumption by running placebo regressions in control districts where there were no broadcasts. If the assumption is correct, we expect \( \beta^4 = \beta^5 = 0 \).

### 5.2.2 DDD across crops, using farmer fixed effects

The second specification exploits variation across space, instead of time. Although both the above assumptions may seem plausible, we might worry about selection of radio ownership being time-variant and different across districts with and without price information broadcasts. This might, for example, be the case if farmers with higher quality crops have a higher demand for price information, and some of the marginal farmers will have bought a radio in response to the introduction of MIS. More generally, farmers with radio in MIS broadcasting districts, as compared to farmers with radio in districts with no MIS broadcasts, might therefore have different unobserved characteristics in 2005. This would then violate the identifying assumptions and bias the results. To address this concern, we exploit variation across crops in triple-differences estimations. Since the

\[ \text{Again, we slightly abuse the notation since we are using logged outcome variables for the total margin and revenue.} \]
MIS did only collect and broadcast information on some, but not all, crops, farmers with radio only received regular price information through radio for some crops. Therefore, we define two groups of crops: MIS crops and non-MIS crops. MIS crops are crops for which district prices were regularly reported on the MIS radio programs and include Maize, Beans, Groundnuts, Cassava, Millet and Sweet potatoes.\textsuperscript{24} Non-MIS crops are crops on which the Market Information Service did not disseminate price information.\textsuperscript{25} Importantly, since many farmers produce more than one crop, this strategy allows us to also use \textit{farmer fixed effects}. That is, this controls for any unobserved farmer characteristic that homogeneously affects farmers’ market activity. We estimate the following equation.

\begin{equation}
\begin{aligned}
y_{icd} = & \beta_1 (r \times ic)_{icd} + \beta_2 (ic \times id)_{icd} + \beta_3 (ic \times id \times r)_{icd} + \delta_i + \mu_{cd} + \epsilon_{icdt},
\end{aligned}
\end{equation}

where $ic_{icd}$ is a dummy variable equal to one if the crop $c$ is a MIS crop (i.e. included in the broadcasts). $\delta_i$ is farmer fixed effects.

\textit{Identifying assumption (equation 36):} First, farmers with radio are informed about market prices for crops that are being broadcast, but uninformed for crops that are not being broadcast. Second, selection into radio ownership is only a function of farmer characteristics (e.g. wealth, literacy, or education).

Under these assumptions, by predictions 2 and 3 we will use OLS to consistently estimate:

- Extensive Margin: $\beta_3 = \beta^p > 0$ and $\beta_2 = \gamma^p < 0$.
- Total Margin: $\beta_3 = \beta^s > 0$ and $\beta_2 = \gamma^s < 0$.
- Farm-Gate Price: $\beta_3 = \beta^p \leq 0$ and $\beta_2 = \gamma^p \leq 0$.

\textsuperscript{24}We coded all radio scripts in 2004 and coded all reports of crop prices. We then calculated the share of reports (out of all reports of crop prices) for each crop during 2004. The main food crops (see Uganda Bureau of Statistics, 2000) maize, beans, groundnuts, cassava, millet, and sweet potatoes were mentioned in the radio scripts 5\% of the times, with prices for maize and beans being reported most often. The MIS project also regularly reported prices for Matooke [plantains or food bananas], but the agricultural module in the household survey data does not code plantains but several types of Matooke (Matooke food, Matooke beer, Matooke sweet), so we cannot link the two data sets for this crop. Note that the popular name for the plantain (food banana) is Matooke, which is also the name for the popular prepared dished of the plantain. Several crops were only reported a handful of times in some districts (less than 1\%) during the year.

\textsuperscript{25}We drop minor non-MIS crops defined as those crops that constitute less than 1 of the reported non-MIS crops in the 2004/2005 crop survey. The following crops are included: Avocado, Cowpeas, Cotton, Field peas, Onions Pawpaw, Peas, Pigeon peas, Pineapple, Plantation trees, Sugarcane, Tobacco, Tomatoes, Vanilla, and Yams. Prices on coffee were reported through UCDA radio broadcast and were consequently not included.
• Revenue: $\beta^3 = \beta^R > 0$ and $\beta^2 = \gamma^R < 0$.

Notice that if the first assumption is violated, so that farmers are informed about crops even though there are no broadcasts, then we will underestimate the true effects. The second assumption is key. We will assess the validity of the assumption by estimating placebo regressions using data from before the broadcast. If the assumption is correct, we expect $\beta^2 = \beta^3 = 0$. However, if there is selection so that the assumption is violated, and this selection is time-invariant, then we should expect the sign of the coefficient to be similar and significant.

### 5.2.3 Small vs. Large Scale: Heterogeneous GE Effects

To further investigate the predicted mechanisms further, we test the prediction that the effect on informed and uninformed farmers will depend on the aggregate number of farmers becoming informed. We test this prediction, we calculate $\bar{r}$ by taking the aggregate fraction of farmers growing MIS crops in the district using the UNHS household data. We run the following specification

(37)

$$y_{icd} = \beta^1 r_i + \beta^2 \bar{r}_d + \beta^3 (r_i \times \bar{r}_d) + \beta^4 (r_i \times id_d) + \beta^5 (id \times \bar{r})_{icdt} + \beta^6 (id \times r_i \times \bar{r})_{icdt} + \mu_c + \epsilon_{icdt}.$$ 

where $r_i$ is a dummy if farmer $i$ owns a radio, $\bar{r}_d$ is the aggregate $r_i$ of the farmers growing MIS crops in the district $d$, and $id_d$ is a dummy indicating if the farmer lives in a participating MIS district. We use crop fixed effects, $\mu_c$, in all specifications. Note that we cannot use district fixed effect since that is collinear with $id \times \bar{r}$.

*Identifying assumption (equation 37):* The identifying assumption is that, conditional on whether the district is broadcasting, selection into radio ownership is uncorrelated with the aggregate fraction of farmers with radio.

Under this relatively strong assumption, we expect the difference between informed and uninformed farmers depends on the aggregate number of informed farmers:

- **Extensive Margin:** $\beta^6 > 0$.
- **Total Margin:** $\beta^6 > 0$.
- **Farm-Gate Price:** $\beta^6 \leq 0$.
- **Revenue:** $\beta^6 > 0$. 

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6 Results

In this section, we present the regression results. We first show the results on urban market prices and then on farm-gate outcomes.

6.1 Urban Market Price

Predictions 1 states that the urban market price will drop when more farmers become informed, since supply increases due to reduced information frictions between farmers and traders. Table 2 presents the results of equation (37). Columns (1)-(4) shows that the effect of price information broadcast on the market price is positive and significant. The estimates indicate that the market price decreases by approximately 10 to 13 percent when prices are broadcasted on the radio. Furthermore, by prediction 1 the effect of broadcasts should be larger the more informed farmers there are. Columns (5) - (8) show that the triple interaction term is negative. The standard errors are larger in regression using larger samples, but the point estimates are very similar. The estimates are significant in columns 6 and 8 (i.e. when using a smaller sample window around the broadcast starting date). We can most easily interpret column (8), where the estimate is an elasticity where a 1 percent increase in the number of informed farmers decreases the market price by 0.36 percent.

Figure 4 runs a set of placebo regressions similar to column (3), but on using a rolling sample window mimicking column (3) where instead there are no changes in broadcasts between the (placebo) pre and post period. The figure include the main specification, at x value equal to zero. We see that only for the main specification is there an effect.

Together, the results are consistent with prediction 1. Prices decrease when farmers become informed about the market price, due to a positive supply shock resulting from decreased frictions between traders and farmers. It is worth noting that it it unlikely that this is the result of a negative demand shock by urban consumers, since there is little reason for them to decrease demand when radio is broadcasting price information in the rural areas. Next, we will investigate the supply shock suggested by Proposition 2 and 3 by using household data directly.

6.2 Farm Gate Outcomes

Table 3 present the results on the extensive margin.

The DDD estimates in columns (1) and (2) are positive (0.103 and 0.089) and significant, consistent with Prediction 2. Using variation across crops, the DDD estimates in columns (3) and (4) are also positive and significant. This is true even in the most restrictive specification using farmer fixed effects (column 4). It is worth pointing out that the estimates in (1)-(4) are also very
similar to each other, which is expected but also lends credibility to the identification strategy. The point estimates imply that farmers that become informed on average increase the likelihood of selling by approximately 8-10 percentage points. This is substantial, considering that the likelihood in the sample is about 0.27-0.30.

To assess the identification assumptions, we also run placebo regressions in districts where there were never any broadcasts (columns 5 and 6), and before there were any broadcasts (columns 7 and 8). None of the DDD estimates are significant and they are close to zero. This lends credibility to the identification strategy.

The DD estimates in columns (1) and (2) are negative (-0.94 and -0.095) and significant, consistent with Prediction 3. Using variation across crops, the DD estimates in columns (3) and (4) are also negative and significant. In the most restrictive specification using farmer fixed effects, we see that the coefficient is positive but insignificant. The point estimates imply that farmers that are uninformed, but live in districts where other farmers become informed, on average decrease the likelihood of selling by approximately 4-9 percentage points. This is a non-trivial amount. The placebo regressions in columns (5) - (8) are all insignificant and small or non-negative. Together, the DD estimates in columns (1) - (8) are consistent with the predictions and indicate that uninformed farmers in equilibrium decrease their likelihood of selling to traders, because of negative price shocks that are the result of positive supply shocks from informed farmers.

Table 4 shows the results for the share of the output sold to the market (and thus not consumed). We see that the results are in general consistent with Prediction 2 and 3. Overall, the estimates show a similar pattern as in table 3, there is a positive supply response by informed farmers relative to uninformed farmers (the DDD estimate is between 0.338 and 0.436), and a negative supply response by uninformed farmers (the DD estimate is between -0.183 and 0.310). Table 5 estimates the effect on the farm gate price. The estimates suggest that informed farmers receive relative higher farm-gate prices than uninformed farmers (the DDD estimate is between 0.149 and 0.385). There is no robust evidence that the intervention lead uninformed farmers to receive a lower farm-gate price (the DD estimate is between -0.122 and 0.035). This is consistent with the model, since the theoretical prediction is ambiguous. The farm-gate price is endogenous to the bargaining with traders and a price is realized conditional on selling. Since the intervention led the market price to fall, uninformed farmers decreased market participation. It thus appears that uninformed farmers only sold their crops when receiving the same farm-gate price as before the intervention. The placebo regressions in columns 5-8 provide evidence that the effects are not driven by omitted variables.

Table 6 shows the estimated impact on farmers’ crop incomes. There is a substantial increase in revenue for informed farmers relative to uninformed farmers. The DDD estimate is between 0.338 and 0.436, implying that the intervention increased informed farmers revenue by 40-55% relative
to uninformed farmers. This would be the estimated treatment effect under the partial equilibrium assumption of unaffected market prices and no negative externalities, since uninformed farmers in treatment districts would provide the proper counterfactual outcomes. However, this conclusion is not valid since the intervention was large-scale and lead to general equilibrium effects. The DD estimate shows the intervention lead to a substantial decrease in crop revenue for uninformed. The most conservative estimates imply there was a 35-55% reduction in crop revenue for farmers without access the broadcasts, but living in districts where other farmers did have access. This is a combination of farm-gate price changes and supply responses, but mainly due to the latter as we see that the effects on prices are insignificant. The placebo regressions in columns 5-8 show that there is no evidence that the effects are driven by omitted variables.

The general equilibrium effects on the market prices is driven by the fact that the intervention was implemented on a large scale, so each districts a large fraction of farmers became better informed. This is also what drives a wedge in farm-gate outcomes between farmers with radio and farmers without radio in the intervention districts. Table 7 provide additional evidence of the proposed mechanism, as the effects on farm-gate outcomes are more pronounced in districts where a large share of the population owned a radio before the intervention begun. The signs of the coefficients in columns 1-4 are consistent with the model, although some of the interaction terms are imprecisely estimated when the variation is at the district level only (the double interaction term).

### 6.3 Aggregate Impact

The results show that the intervention had distributional consequences: consumers benefited from lower prices; farmers with access to radio benefited from higher farm revenues, while crop income fell for farmers without access to radio. To assess the aggregate impact on farm revenue, we conduct counterfactual calculations. For each observation in the sample of farmers in treatment districts, and crops that were part of the information campaign, the counterfactual outcomes is calculated using the DD and DDD coefficients in table 6 (column 3) and calculating what the revenue would have been in the absence of the intervention. The counterfactual observations are then summed for the aggregate effects in the (representative) sample. Table 8 shows the results. The actual total revenue in the sample is 141.2 million Ugandan shillings. The counterfactual estimate is 144.1 million shillings. The aggregate effect of the intervention is thus negligible (-2%). This can be compared to the partial equilibrium conclusion that the intervention lead to a 40-55% increase in revenue for farmers with access to the radio (and no effect farmers without access), which would have been drawn under the partial equilibrium assumption of unaffected market prices and no negative spillovers on uninformed farmers. Thus, when taking the general equilibrium effects into account, the interventional had negligible effects on the average farmer
incomes, but large distributional consequences.

### 6.4 Alternative Mechanisms

In this section, we investigate other potential explanations for the results. First, we consider that the broadcast did not only affect outcome by providing price information. Instead, it may be that the radio programs also provided farmers with information that had direct effect on agricultural productivity, by teaching farmers about farming techniques. This could affect quantity sold, quantity produced, as well as the quality of the crops (which could increase the farm-gate price). We use the UNHS 2005 survey quiz on agricultural technology knowledge to test for the hypothesis that the broadcast informed farmers about farming technique. Column (1) presents the results using the fraction of correct answers on the quiz. We find no evidence on technology learning.

Second, we consider the alternative that the price information changed where the farmer sold their output. In principle, if risk averse farmers become informed about the market price, they may be more likelihood to travel directly to the district market to sell their crops. Columns (2) - (4) present the results. We find no evidence of a change in where the goods are sold.\(^{26}\)

Finally, we investigate whether the price information made farmers produce more of the crops for which there was price information. If changing the composition of crops produced is costless for the farmer (by increasing the plot area for crops with price information and decreasing it for crops without price information), we would expect output to increase which, in turn, could affect the farm-gate outcomes. However, unless higher production is also associated with higher share of output sold, such a production effect would tend to work against finding an effect on s. Columns (5) - (7) show the results. We find no evidence of production behavior on average.\(^ {27}\)

### 7 Concluding Remarks

The paper provides an example where sensible conclusions made in partial equilibrium are offset by general equilibrium effects. In addition, this paper finds that price information plays an important role in facilitating market exchange. The functioning of agricultural markets is central to the development of low income countries. How to boost agriculture production in developing countries has been an ongoing policy question. The question is of particular importance for countries in sub-Saharan Africa where the growth in agricultural yield has been stagnant. While the academic

\(^{26}\)We run the same regressions using a dummy indicating if the farmer sold the crops to a private trader in the village. We find no evidence of changed behavior.

\(^{27}\)This could be explained either by significant adjustment costs or by beliefs that the price information broadcasts would terminate. Also, we cannot rule out changes in output within the group MIS crops.
literature on the subject is extensive, existing research has primarily focused on two broad sets of explanations: the low technology adoption rate (of technologies such as HYV crops, irrigation and fertilizers) and the functioning of agricultural markets.

The issue of functioning markets was a prime concern behind the reforms of the agricultural markets in many sub-Saharan Africa countries in the late 1980s and 1990s. However, the supply response from liberalizing agricultural markets has been weaker than expected. One explanation that has been put forward for this low supply response is that the pre-liberalization period where the government essentially fixed a price for key food and cash crop commodities (often a price well below the market price) has been replaced by a situation where better informed (at least about local market conditions) local traders are able to force down prices to farmers with little idea of price movements and market trends. Our results are at least qualitatively consistent with this claim.

The effects of information on outcomes are interesting from an economic theory perspective. However, the effects are also relevant for the discussion about the role of information and communication technologies (ICTs) for economic development (cf. Jensen, 2007). Living standards for most of the world’s poorest are largely determined on how much they get paid for their output, mainly crops. Thus, the functioning of output markets is central to the income for farmers engaged in agriculture in low-income countries. In most developing countries, markets are dispersed and the infrastructure is poor. Small-scale producers typically lack information on market prices, so that the potential for inefficiency in the allocation of goods across markets and the allocation between consumption and trading is large.

Moreover, asymmetric information between sellers (i.e. poor small-scale farmers) and buyers adds important distributional concerns. By improving the access to information, ICTs may help poorly functioning markets work better, improve farmers’ bargaining positions, and thereby increase the incomes of the poor. In addition, our results suggest that urban consumers, through lower prices, indirectly benefit from the better functioning. However, access to price information seldom reaches everyone, and it is still an open question to what extent farmers with little access to information are affected when a large part of the rural population gets access to good information. Our results show that price information can have substantial general equilibrium effects, pushing prices downward. Whether poor farmers without access to information decrease their integration with markets and become even poorer as a consequence of lower prices is a potentially important question for future research.
8 References


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Appendix

A.1. Details on the propositions

\[ MIS_{PE}[x(m)] = E \left[ x^I(m) - x^U(m) \right] \]
\[ MIS_{GE}^I[x(m)] = E \left[ x^I(m(r)) - E x^U(m(0)) \right] \]
\[ MIS_{GE}^U[x(m)] = E \left[ x^U(m(r)) - E x^U(m(0)) \right] \]
\[ \Delta MIS_{GE}[x(m)] = E \left[ x^I(m(r)) - x^U(m(r)) \right] \]

Note that \( MIS_{GE}^I = \Delta MIS_{GE} + MIS_{GE}^U \).

\[ \frac{\partial MIS_{GE}^I}{\partial r}; \frac{\partial MIS_{GE}^U}{\partial r}; \text{ and } \frac{\partial \Delta MIS_{GE}}{\partial r} \]

We summarize the predictions for our main outcome variables: market participation, proxied by share sold, \( s(m) = q(m)/Q \), the extensive margin \( \rho \), farm-gate prices \( p(m) \), and market prices \( m \), below. All proofs are in appendix.

To arrive at a closed form solution for the market prices, we assume that \( u(c) \) is quadratic; i.e., \( u(c) = a(Q - q) - b(Q - q)^2 \).

Taking the total derivative of (26)-(28) with respect to \( r \) yields

\[ \frac{\partial m^*_1}{\partial r} = -\frac{q^I_1(m^*_1)}{\delta + r \frac{\partial q^I_1(m^*_1)}{\partial m^*_1}} < 0 \]

\[ \frac{\partial m^*_2}{\partial r} = \frac{q^U_2(m^*_2, m^*_3) - q^I_1(m^*_1)}{\delta + r \frac{\partial q^I_1(m^*_1)}{\partial m^*_2} + (1 - r) \frac{\partial q^U_2(m^*_2, m^*_3)}{\partial m^*_2}} < 0 \]

\[ \frac{\partial m^*_3}{\partial r} = 0. \]
The mean market price is

\[ E [m] = \sum_{j=1}^{3} \pi_j m_j^*. \]

Thus

(A24) \[ \frac{\partial E [m]}{\partial r} = \pi_1 \frac{\partial m_1^*}{\partial r} + \pi_2 \frac{\partial m_2^*}{\partial r} < 0 \]

For share sold we have

\[ MIS^{UL}_{GE} [s^U(m)] = \frac{1}{Q} E \left[ q^U(m^*(r)) \right] - \frac{1}{Q} E \left[ q^U(m^*(0)) \right] \]

\[ = \frac{1}{Q} \rho_2 \left[ (m^* (r))q^U_2 (m^*(r)) - (m^*(0))q^U_2 (m^*(0)) \right] < 0 \]

as \( \partial q^U_2 (m^*(r)) / \partial r < 0. \)

\[ MIS^{IL}_{GE} [s^I(m)] = \frac{1}{Q} E \left[ q^I(m^*(r)) \right] - \frac{1}{Q} E \left[ q^I(m^*(0)) \right] \]

\[ = \frac{1}{Q} \rho_2 \left[ q^I_2 (m^*(r)) - q^I_2 (m^*(0))q^U_2 (m^*(0)) \right] + \frac{1}{Q} \rho_3 \left[ (m^*(r))q^I_3 (m^*(r)) \right] > 0 \]

as \( q^I_2 > 1 > q^U_2. \)

\[ \Delta MIS_{GE} [s(m)] = \frac{1}{Q} E \left[ q^I(m) \right] - \frac{1}{Q} E \left[ q^U(m) \right] \]

\[ = \frac{1}{Q} \rho_2 \left[ q^I_2 (m^*(r)) - q^I_2 (m^*(0))q^U_2 (m^*(0)) \right] + \frac{1}{Q} \rho_3 \left[ (m^*(r))q^I_3 (m^*(r)) \right] > 0 \]

\[ p^U_L = m_L \]

and

\[ p^U_H = m_H - \frac{q^H_L}{q^H} (m_H - m_L) \]
The first-order conditions for \((q_1, R_1)\) are

\[
\frac{dL}{dq_1} = -\pi_1 u'(Q - q_1) + \lambda_1 m_1 - \lambda_2 m_2 + \mu m_1 = 0
\]

and

\[
\frac{dL}{dR_1} = \pi_1 - \lambda_1 + \lambda_2 - \mu = 0
\]

The first-order conditions for \((q_2, R_2)\) are

\[
\frac{dL}{dq_2} = -\pi_2 u'(Q - q_2) + \lambda_2 m_2 - \lambda_3 m_3 = 0
\]

and

\[
\frac{dL}{dR_2} = \pi_2 - \lambda_2 + \lambda_3 = 0
\]

The first-order conditions for \((q_3, R_3)\) are

\[
\frac{dL}{dq_3} = -\pi_3 u'(Q - q_3) + \lambda_3 m_3 = 0
\]

and

\[
\frac{dL}{dR_3} = \pi_3 - \lambda_3 = 0
\]
\[ \frac{\partial m_2^*}{\partial r} = \frac{q_2^U q_2^{UL} - q_2^I}{\delta + r \frac{\partial q_2^I}{\partial m_2^*} + 2(1 - r)q_2^U \frac{\partial q_2^{UL}}{\partial m_2^*}} < 0 \]

(47) \[ d - \delta m_1^* + \epsilon_1 = rq_1^I(m_1^*) \]

(48) \[ d - \delta m_2^* + \epsilon_2 = rq_2^I(m_2^*) + (1 - r)q_2^{UL}(m_2^*, m_3^*) \]

(49) \[ d - \delta m_3^* + \epsilon_3 = q_3^I(m_3^*) \]

to
Figure 1. Districts with the Market Information Service
Figure 2. The upper panel plots the weekly market price of beans across districts in 2001 (i.e. before the start of broadcasts is most districts). The bottom panel plots the same for millet. The price is in Ugandan shillings. The graphs show that there is substantial price variation across districts at any given point in time, as well as across time within districts.
Figure 3. The figure shows weekly mean standardized market prices for the main crops in early information districts (Info Districts) and late districts (Non-Info Districts). The broadcasts for the early districts began in February 2002 (the exact week is unknown). The broadcasts for the late districts began after July 2002.

Figure 4. Main and Placebo Estimates of Broadcasts on Market Prices. The figure shows the estimated coefficients and 95 percent confidence intervals on the interaction between InfoDistrict and Post for the main regression and 32 placebo regressions, using 2001-02 weekly price data for the main crops. Each placebo regression is done with a sample of eight weeks, where the first four weeks are defined as the (placebo) pre period (Post=0) and the last four weeks are defined as the post period (Post=1). To mimic the main regression, the pre and post period is separated by four weeks. The estimated coefficient value is on the y-axis. The x-axis refers to the placebo sample window used for each estimate, where zero is the main regression. The negative values on the x-axis are the placebo regressions using samples before the broadcasts started, where the absolute value refers to the number of weeks between the last week in the sample and the first week of the broadcasts. Similarly, the positive values on the x-axis are the placebo regressions using samples after the broadcasts started, where the value refers to the number of weeks between the first week in the sample and the start of the broadcasts. There are only eight placebo regressions in the Post-period because broadcasts began in the control districts for later weeks.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<td>InfoDistrict x Post</td>
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<td>-0.131***</td>
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<td>-0.165***</td>
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<td></td>
<td>(0.062)</td>
<td>(0.060)</td>
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<td>(0.045)</td>
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<td>InfoDistrict x Post x RadioFarmers</td>
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<td>-0.008**</td>
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<td></td>
<td></td>
<td></td>
<td>-0.380</td>
<td>-0.360**</td>
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<td></td>
<td></td>
<td></td>
<td>-0.327</td>
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<tr>
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<td>log(RadioFarmers) x Post</td>
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<td></td>
<td>0.327</td>
<td>0.235*</td>
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<td>(0.257)</td>
<td>(0.136)</td>
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<td>8</td>
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<td>8</td>
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<td>341.7</td>
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<td>337.8</td>
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<td>39</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td>39</td>
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</tbody>
</table>

Notes: The data is at the district-crop-week level. Each sample contains sixteen or eight weeks of market price data from 2002 for each district-crop. InfoDistrict is a dummy variable indicating if the district started broadcasting in February 2002 (the exact dates unknown), and zero if the district started broadcasting later (after July 2002). In the main regressions, Post is a dummy variable equal to one if the data is from March and equal to zero if it is from January. RadioFarmers measures the aggregate percentage of farmers in the district growing the crop that own a radio, taken from the 1999/2000 Uganda National Household Survey. The variable is demeaned. The crops are Beans, Cassava, Groundnuts, Maize, Millet, and Sweet Potatoes. The samples contains eight MIS districts where the broadcasting start month is known, of which five started broadcasting in February 2002 (the exact date is unknown) and three after July 2002. Robust standard errors in parentheses, clustered at the district-crop level. *** p<0.01, ** p<0.05, * p<0.1.
### Table 3. Effects at the Farm-Gate: Extensive Margin

<table>
<thead>
<tr>
<th></th>
<th>Main regressions</th>
<th>Placebo regressions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>InfoCrop x Post x RadioFarmer</td>
<td>0.103**</td>
<td>0.089**</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>InfoCrop x Post</td>
<td>-0.094**</td>
<td>-0.095**</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>InfoCrop x InfoDistrict x RadioFarmer</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>InfoCrop x InfoDistrict</td>
<td>-0.065**</td>
<td>-0.042</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.034)</td>
</tr>
</tbody>
</table>

| Observations                         | 23,852           | 23,852 | 31,537 | 31,537 | 29,362 | 29,362 | 21,677 | 21,677 |
| R-squared                            | 0.113            | 0.119  | 0.116  | 0.363  | 0.131  | 0.141  | 0.150  | 0.525  |
| Sample Years                         | Pre&Post         | Pre&Post | Post | Post | Pre&Post | Pre&Post | Pre | Pre |
| Sample Districts                     | Info             | Info | All | All | All | All | All | All |
| Sample Crops                         | All | All | All | All | All | All | All | All |
| Crop FE                              | Yes           | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE                          | Yes           | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| District x Post FE                   | No            | Yes | No | No | No | Yes | No | No |
| Crop x Season FE                     | No            | Yes | No | Yes | No | Yes | No | Yes |
| Farmer FE                            | No            | No | No | Yes | No | No | No | Yes |
| Dependent Variable Mean              | 0.302          | 0.302 | 0.267 | 0.267 | 0.285 | 0.285 | 0.331 | 0.331 |

Notes: *InfoCrop* indicates that the crop belongs to the crops which the MIS broadcast price information for, and zero otherwise. *Post* is a dummy variable equal to one if the sample year is 2005 (i.e. after the market information broadcasting started), and zero if it is 1999 (i.e. before the broadcasting started). *RadioFarmer* is a dummy variable indicating whether the farmer owns a radio. *InfoDistrict* is a dummy variable indicating if the farmer lives in a MIS district, and zero otherwise. All regressions include a full set of main effects and interaction effects (Results not shown for brevity. The coefficients are in general insignificant). Sample districts equal to All includes both districts with and without the market information service. *Selling any Output* is a dummy variable indicating if the farmer sold any of the crop output, and zero otherwise. The data is at the plot level, from Uganda National Household Survey. There are two growing seasons per year. Robust standard errors in parentheses, clustered at the district-crop level in regressions 1-2 and 5-6 (there are 17 info districts and 221 district-crop clusters) and clustered at the district level in regressions 3-4 and 7-8 (56 clusters). *** p<0.01, ** p<0.05, * p<0.1.
<table>
<thead>
<tr>
<th>Table 4. Effects at the Farm-Gate: Share of Output Sold</th>
<th>Dependents Variable: Log(Share of the output sold)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Main regressions</td>
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<td>(1)</td>
</tr>
<tr>
<td>InfoCrop x Post x RadioFarmer</td>
<td>0.436**</td>
</tr>
<tr>
<td></td>
<td>(0.183)</td>
</tr>
<tr>
<td>InfoCrop x Post</td>
<td>-0.301*</td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
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<tr>
<td>InfoCrop x InfoDistrict x RadioFarmer</td>
<td>0.405***</td>
</tr>
<tr>
<td></td>
<td>(0.142)</td>
</tr>
<tr>
<td>InfoCrop x InfoDistrict</td>
<td>-0.276**</td>
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<tr>
<td></td>
<td>(0.133)</td>
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<tr>
<td>Observations</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.137</td>
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<tr>
<td>Sample Years</td>
<td>Pre&amp;Post</td>
</tr>
<tr>
<td>Sample Districts</td>
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</tr>
<tr>
<td>Sample Crops</td>
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<tr>
<td>Crop FE</td>
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<tr>
<td>District FE</td>
<td>Yes</td>
</tr>
<tr>
<td>District x Post FE</td>
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</tr>
<tr>
<td>Crop x Season FE</td>
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<tr>
<td>Farmer FE</td>
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<td>Dependent Variable Mean, level</td>
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</table>

Notes: Data definitions and specifications are the same as table 3. Robust standard errors in parentheses, clustered at the district-crop level in regressions 1-2 and 5-6 (there are 17 info districts and 221 district-crop clusters) and clustered at the district level in regressions 3-4 and 7-8 (56 clusters). *** p<0.01, ** p<0.05, * p<0.1.
### Table 5. Effects at the Farm-Gate: Farm-Gate Price

<table>
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<tr>
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<th>Placebo regressions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
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<tr>
<td>InfoCrop x Post x RadioFarmer</td>
<td>0.151</td>
<td>0.149</td>
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<tr>
<td></td>
<td>(0.137)</td>
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<tr>
<td></td>
<td>(0.166)</td>
<td>(0.147)</td>
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<tr>
<td>InfoCrop x InfoDistrict x RadioFarmer</td>
<td>0.385***</td>
<td>0.456*</td>
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<tr>
<td></td>
<td>(0.119)</td>
<td>(0.238)</td>
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<tr>
<td>InfoCrop x InfoDistrict</td>
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<td>R-squared</td>
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<td>District x Post FE</td>
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<td>Crop x Season FE</td>
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<td>Farmer FE</td>
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<td>Dependent Variable Mean</td>
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Notes: Data definitions and specifications are the same as table 3. Robust standard errors in parentheses, clustered at the district-crop level in regressions 1-2 and 5-6 (there are 17 info districts and 221 district-crop clusters) and clustered at the district level in regressions 3-4 and 7-8 (56 clusters). *** p<0.01, ** p<0.05, * p<0.1.
### Table 6. Effects at the Farm-Gate:

**Crop Revenue**

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</thead>
<tbody>
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<td>(2)</td>
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<tr>
<td><strong>InfoCrop x Post x RadioFarmer</strong></td>
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<td>0.575**</td>
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<tr>
<td></td>
<td>(0.270)</td>
<td>(0.270)</td>
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<td><strong>InfoCrop x Post</strong></td>
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<td>-0.781***</td>
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<tr>
<td></td>
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<td>(0.284)</td>
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<td><strong>InfoCrop x InfoDistrict x RadioFarmer</strong></td>
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<tr>
<td><strong>InfoCrop x InfoDistrict</strong></td>
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</tbody>
</table>

Notes: Data definitions are the same as table 3. Robust standard errors in parentheses, clustered at the district-crop level in regressions 1-2 and 5-6 (there are 17 info districts and 221 district-crop clusters) and clustered at the district level in regressions 3-4 and 7-8 (56 clusters). *** p<0.01, ** p<0.05, * p<0.1.
<table>
<thead>
<tr>
<th>Effects at the Farm-Gate: Heterogeneous GE Effects as a Function of Aggregate Fraction of Informed Farmers</th>
<th>Selling any Output, Dummy</th>
<th>Log(Share of the output sold)</th>
<th>Log(Revenue, Ush)</th>
<th>Farm-Gate Price, Normalized</th>
</tr>
</thead>
<tbody>
<tr>
<td>InfoDistrict x RadioFarmer x %RadioFarmers</td>
<td>0.379**</td>
<td>1.461**</td>
<td>2.844**</td>
<td>-0.753</td>
</tr>
<tr>
<td></td>
<td>(0.181)</td>
<td>(0.708)</td>
<td>(1.394)</td>
<td>(0.535)</td>
</tr>
<tr>
<td>InfoDistrict x %RadioFarmers</td>
<td>-0.268</td>
<td>-1.034</td>
<td>-1.933</td>
<td>0.477</td>
</tr>
<tr>
<td></td>
<td>(0.200)</td>
<td>(0.767)</td>
<td>(1.491)</td>
<td>(0.698)</td>
</tr>
<tr>
<td>Observations</td>
<td>29,210</td>
<td>29,210</td>
<td>29,168</td>
<td>6,957</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.024</td>
<td>0.026</td>
<td>0.026</td>
<td>0.018</td>
</tr>
<tr>
<td>Sample Years</td>
<td>Post</td>
<td>Post</td>
<td>Post</td>
<td>Post</td>
</tr>
<tr>
<td>Sample Districts</td>
<td>All</td>
<td>All</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>Sample Crops</td>
<td>Info</td>
<td>Info</td>
<td>Info</td>
<td>Info</td>
</tr>
<tr>
<td>Crop FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>District FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>District x Post FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Crop x Season FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Farmer FE</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

Notes: The data is at the plot level, from Uganda National Household Survey. *RadioFarmer* is a dummy variable indicating if the farmer owns a radio. *RadioFarmers* measures the percentage of farmers in the district growing the crop that own a radio, taken from the 1999/2000 Uganda National Household Survey. The variable is demeaned. The specification includes a full set of main effects and interaction effects (results not shown, available upon request). Robust standard errors in parentheses, clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.
<table>
<thead>
<tr>
<th>Table 8. Aggregate Effect on Farmer Income</th>
<th>Total crop revenue in the sample, million Ush</th>
<th>Counterfactual total crop revenue, million Ush</th>
<th>Aggregate effect, million Ush</th>
<th>Aggregate effect, percent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Informed Farmers</td>
<td>114.7</td>
<td>101.6</td>
<td>13.1</td>
<td>12.9%</td>
</tr>
<tr>
<td>Uninformed Farmers</td>
<td>26.5</td>
<td>42.5</td>
<td>-16.0</td>
<td>-37.6%</td>
</tr>
<tr>
<td><strong>Aggregate, Total</strong></td>
<td><strong>141.2</strong></td>
<td><strong>144.1</strong></td>
<td><strong>-2.9</strong></td>
<td><strong>-2.0%</strong></td>
</tr>
</tbody>
</table>

Notes: The sample consists of farmers in MIS districts that grow MIS crops. For each farmer-plot observation in the sample, the counterfactuals are calculated using the DD and DDD point estimates and calculating what the revenue would have been in the absence of MIS intervention. The numbers shown for informed and uninformed farmers are the sums when aggregating across all observations within each type of farmer.