Farmer Bargaining Power and Market Information Services

Pierre Courtois and Julie Subervie

In many Sub-Saharan African countries, farmers typically have a choice between selling their products to traders who travel between villages and markets and transporting their products to the nearest market themselves. Because of communities' remoteness and poor communications with marketplaces, farmers' uncertainty about market prices is usually high. Traders may take advantage of farmers' ignorance of the market price and extract a rent from them by offering very low prices for their products. In this article, we model bargaining interactions between farmers and traders meeting at the farmgate and we study how price information affects the bargain and the balance of power. We show the conditions for Market Information Services (MIS) to be profitable for farmers and examine efficiency issues associated with asymmetric information. Finally, we test the model's prediction that information results in positive individual gain for farmers using original survey data collected in the Northern region of Ghana. Specifically, we estimate the causal effect of a mobile-based MIS program on farmers' marketing performances and find that farmers who have benefited from the MIS program received significantly higher prices for maize and groundnuts: about 10% more for maize and 7% more for groundnuts than what they would have received had they not participated in the MIS program. These results suggest that the theoretical conditions for successful farmer use of MIS may be met in the field.

JEL codes: D81, D83, O12, O13, C78.

The price that smallholders receive for their agricultural products has great implications for poverty alleviation. Increased profitability for farmers may lead them to change their production, investment, and marketing decisions: they may farm land more intensively, sell in larger quantities, invest in productive assets, adopt new agricultural technologies, move land out of nonagricultural use, switch crops, or engage in spatial arbitrage (Jensen 2010). In many sub-Saharan African countries, farmers typically have a choice between selling their products to traders who travel back and forth between villages and markets or transporting their products themselves to the nearest market (Fafchamps and Hill 2005). Many farmers opt for trader pick-up, despite the fact that traders may take advantage of their ignorance of the market price, seeking to extract a rent from them by offering very low prices for their products (Fafchamps and Hill 2008; Mérel, Sexton, and Suzuki 2009). Previous studies have examined how farmers decide whether or not to participate in the market (Bellemare and Barrett 2006; Goetz 1992; Key, Sadoulet, and Janvry 2000), as well as how they choose between trader pick-up and market delivery when selling their products (Fafchamps and Hill 2005). A common feature of these studies is that they focus on transportation costs as the main determinant in marketing decisions. One reason for this is that transportation costs are known to be very high in

---

Pierre Courtois is researcher at INRA, the French Institute for Research in Agriculture, UMR 1135 LAMETA, F-34000 Montpellier, France. Julie Subervie is researcher at INRA, the French Institute for Research in Agriculture, UMR 1110 MOISA, F-34000 Montpellier, France. This research would not have been possible without the full cooperation of Esoko-Ghana. We are particularly grateful to Sarah Bartlett and Isaac Boateng for their research assistantship in the field. Further, we wish to thank the editor and two anonymous referees for their comments and helpful suggestions as well as seminar participants at CSAE Conference 2013 on Economic Development in Africa, the 15th Annual BIOECON Conference on Conservation and Development, DIAL Development Conference 2013 on Institutions and Development, and invited seminars at Toulouse School of Economics and the CIRED research unit. Funding for this research was provided by the French Agency for Development (AFD) and the Technical Centre for Agricultural and Rural Cooperation (CTA).
Correspondence may be sent to: subervie@supagro.inra.fr.

Amer. J. Agr. Econ. 97(3): 953–977; doi: 10.1093/ajae/aau051
Published online June 22, 2014
© The Author 2014. Published by Oxford University Press on behalf of the Agricultural and Applied Economics Association. All rights reserved. For permissions, please e-mail: journals.permissions@oup.com

sub-Saharan Africa,[1] making them a critical component in a farmer's marketing decisions. Information about market prices is another key determinant. Yet, farmers usually lack information about current market prices because of villages' remoteness and poor communications with marketplaces. When analyzing the role of transaction costs in the farmer's decision to sell to the trader rather than at the market, Fafchamps and Hill (2005) assume that the farmer must choose between receiving a lower price at the farmgate and receiving a higher price at the market while incurring a transaction cost. The fact that the farmer does not have the necessary price information to engage in optimal trade or arbitrage is relatively poorly investigated. Now that most African farmers have the opportunity to use mobile phones for marketing purposes (Aker and Mbiti 2010; Goyal and González-Velosa 2012), a relevant research question would seek to better understand how price information affects bargaining and the balance of power in the farmer–trader relationship.

Although in 1999 only 10% of African people had mobile phone coverage, by 2008 more than 65% of the population had access to this service. It is often argued that mobile technology is likely to considerably reduce the search costs faced by farmers. With mobile phones, farmers obtain price information for the cost of sending a text message or making a call. This should cause traders visiting farmers at the farmgate to raise the price they are willing to pay for farmer products, an outcome which would result in a welfare transfer from traders to farmers. This accounts for why, along with the Information and Communication Technology (ICT) boom, Market Information Services (MISs) working through mobile phone networks have emerged in some developing countries. These MISs are provided by private companies from ICT sectors such as mobile network operators or software developers and sometimes by governments. They offer their users market information services, such as SMS alerts on current market prices.[2] In Ghana, an Accra-based private company has operated an MIS program called Esoko since 2008. This new generation of MIS marks an advancement over previous services[3] because it provides users customized and detailed price information on a weekly basis (United States Agency for International Development [USAID 2010]). This article seeks to understand how MIS can lead to farmers receiving higher prices for their agricultural products.

We begin our study by modeling the bargaining interactions between a farmer and a trader. Related to the work of Fafchamps and Minten (2012), the question we aim to tackle here is as follows: How much would an informed farmer receive in terms of price gain compared with a situation without price information? We set the assumptions of the model based on our own observations from field work, as well as from the relevant literature describing bargains at the farmgate in the northern region of Ghana (Al-Hassan, Dorward, and Poulton 1999; Aryeetey and Nyanteng 2006) and data from the Ghana Living Standard Survey. Our model describes a two-player, two-period, offer–offer schema with asymmetric information. The bargain we study occurs at the farmgate in a finite sequence of two periods over the course of a day. In this framework, the farmer does not know the market price with certainty unless he subscribes to the MIS, whereas the trader is always fully informed. When the farmer does not subscribe to the MIS, he assigns a probability to each possible state of the market price and accepts or rejects the offers of the trader according to his expectations as well as his transportation costs. We solve the game by backward induction and compare the equilibriums reached with and without MIS. If the market price is high, the model predicts that the individual gain to the farmer from being informed is positive. The reason for this is that the uninformed farmer assigns a nonzero probability to the

[1] Recent studies indicate that transportation costs are much higher in sub-Saharan Africa than in other regions (Teravaninthorn and Raballand 2009). It has also been noted that transportation costs over short distances (e.g., from the farm to the local market) are much higher than long-distance transportation costs, presumably because the vehicles are smaller and road quality is poorer (World Bank 2009). In addition, it appears that West African countries often have a relatively well-connected road network compared with East African countries (Dorosh et al. 2010).

[2] There are several examples of companies providing SMS-based market information services in developing countries: Manobi in Senegal, CellBazaar in Bangladesh, KACE in Kenya, and Reuters Market Light in India.

[3] During the 1980s, MISs in Africa were centrally managed by government departments or projects and were mainly aid-funded. Such MISs operated primarily through information boards or radio programs. This first generation of MISs often faced financial and technical difficulties, which undermined the proper functioning of the system, affecting information reliability and timeliness.

low-price state, which the trader exploits by offering a low price. Symmetrically, if the market price is low, the model predicts that the individual gain for the farmer from being informed is negative. This is because the uninformed farmer assigns a nonzero probability to the high-price state, whereas the market price is actually low. To secure the deal, the trader is forced to offer a higher price compared with the situation in which the farmer is informed. In this case, asymmetric information can even lead to a deal failure as soon as the profitability condition of the trader no longer holds. Such a situation never occurs when both agents are informed.

We test the model's prediction that information results in positive individual gain for the farmer using original survey data collected in the northern region of Ghana. Our study examines the causal effect of a mobile MIS-based program on farmers' marketing performances in 2009, a year when market prices were high compared with previous years. We apply the difference-in-difference matching estimator to our data and find that farmers who had access to the mobile-based MIS program received significantly higher prices for maize and groundnuts in 2009: approximately 10% more for maize and 7% more for groundnuts than what they would have received had they not participated in the MIS program. These results suggest that the theoretical conditions for successful farmer use of MIS may be satisfied in the field.

The literature that deals with the impact of MIS on economic development in poor countries can be divided into two categories. Articles of the first category analyze how MIS improves spatial arbitrage (i.e., welfare gains). To our knowledge, the most cited study on the topic is Jensen (2007). Jensen studies fisheries in India, where fishermen at sea are unable to observe prices in coastal markets. Fishermen sell their catch almost exclusively in their local market because of high transportation costs and nonexistent storage capacity. This induces price gaps across markets in excess of transportation costs, resulting in an inefficient welfare state because fish supply varies across markets. The author shows that the introduction of mobile phone service between 1997 and 2001 led to a considerable reduction in fish market price dispersion, the complete elimination of waste, and near-perfect adherence to the Law of One Price. On the same line, Aker and Fafchamps (2013) find that mobile phone coverage reduced the spatial dispersion of producer prices by 6% for a semiperishable commodity (cowpea), and Aker (2010) provides estimates of the impact of mobile phones on price dispersion across grain markets in Niger. The second category is comprised of articles concerned with the impact of MIS on surplus sharing. Svensson and Yanagizawa (2009) address the market power issue by estimating the impact of a radio-based MIS on Ugandan farmers. Contrary to what one might expect from a first-generation MIS, the authors show that access to the radio program strongly improves farmers' bargaining power at the farmgate, increasing farmers' prices by 15%. Goyal (2010) estimates the impact of providing price information to Indian farmers in a framework where farmers sell their soybeans in local wholesale markets in which traders possess price information across markets and farmers do not. The author shows that the introduction of Internet kiosks providing price information translates to a 1% to 3% increase in farmer prices and a 33% increase in profit.

To our knowledge, the first evaluation of a mobile-based MIS was conducted by Fafchamps and Minten (2012). The authors consider not only the bargaining power channel but also the spatial arbitrage channel. Running a randomized controlled trial to test whether Indian farmers who are MIS users obtain higher prices for their agricultural output, they find a zero impact.[4] However, as the authors underline in their conclusion, larger impacts are possible in other contexts, in particular in less competitive and more segmented markets where farmers sell a substantial share of their produce. Consequently, one contribution of our article is to provide one of the first impact evaluations of a mobile-based MIS in an African context. First, we model bargaining interactions between farmers and traders aiming to reach a deal at the farmgate. Second, we present the empirical framework. Finally, we present the results of the econometric analysis and our conclusions.

---

[4] Recent working papers on the same subject includes Nakasone (2013) and Cole and Fernando (2012).

The Model

We model bargaining interactions between farmers and traders aiming to reach a deal at the farmgate. To study how MISs affect bargained prices, we first consider the case where the farmer subscribes to an MIS. We then solve the game with incomplete information. Finally we compare equilibriums with and without subscription to an MIS.

Preliminaries

In Ghana, as in many sub-Saharan African countries, most farmers sell maize at the farmgate (Al-Hassan, Dorward, and Poulton 1999).[5] They sell their products to resident traders who go to farms to buy crops and bring them to local assembly markets to sell to long-distance traders. We begin our analysis by specifying the utility of the two agents making a deal at the farmgate. The farmer, denoted by subscript F, produces an agricultural good. He admits limited storage capacity[6] and can either sell his production at the farmgate or at the market. The trader, denoted by subscript T, buys the agricultural good from the farmer at the farmgate and then sells it at the market. Traveling to the market is costlier for the farmer than for the trader because farmers must usually walk or cycle, whereas traders transport products using a pick-up truck. Some farmers may afford to hire a private transport, whereas others make use of public transportation, carrying along their bag of maize on a tro-tro minivan. However, neither of these means is reported as a common practice in our data. We denote c, the transportation cost incurred by a farmer when traveling to the market, and m, the transportation cost incurred by the trader, with $m < c$. The farmgate price p we refer to in the model is the price for buying the entire amount of product offered by the farmer. We denote the market price as p^m and we assume that, because of transportation and transaction costs, this price is necessarily higher than the farmgate price p. We also assume the market price to be exogenous to our model. According to uncontrollable exogenous elements such as weather and the demand curve (Moschini and Hennessy 2001), the market price can be high ($p^m = p^{m+}$) or low ($p^m = p^{m-}$), with $p^{m+} > p^{m-} > 0$.

By assumption, a farmer never sells goods at a lower price than his cost because producing and selling crops ought to be profitable. The farmer accordingly has a reservation price that we denote as s, with $s \leq p$. As for the farmer, we assume the trader expects the transaction to be profitable, meaning that he accepts a deal if it covers his transportation costs ($p \leq p^m - m$). Because we set $p^m \geq p + m$ and $m < c$, it follows that a Pareto improving agreement always exists between the two agents. Although they share a common interest to reach a deal, they have conflicting ideas over what constitutes a good deal. Whereas the trader prefers buying at the lowest possible price, the farmer prefers to sell at the highest possible price. In other words, the two players conflict over the price p that they seek agreement upon and, therefore, over how to share the rent. Finally, both agents are subject to impatience and prefer an immediate deal to a postponed deal. We set a discount factor δ to measure this impatience, where $\delta \in [0, 1]$. The lower this factor, the more impatient the agents and the lower their utility because of a transaction delay.[7] Formally, the objective functions of the two agents can be written as:

$$\begin{cases} U_T(p,t) = \delta_T^{t-1}[p^m - m - p_t] \\ U_F(p,t) = \delta_F^{t-1}[p_t - s] \end{cases}$$

where t denotes the period at which the deal is made. By assumption, the larger the trader's net benefit $p^m - m - p_t$ from making a deal and the faster this deal is achieved, the greater the trader's utility. Conversely, the larger the price obtained and the lower the production cost, the greater the farmer's utility. Note that all variables are exogenously set except p_t.

We then define the bargaining procedure and the information structure we consider. We base our assumptions on the general picture provided by Al-Hassan, Dorward, and Poulton (1999) and by Aryeetey

[5] They may also sell their production at the local market. However, data from the Ghana Living Standard Survey show that 90% of the sampled farmers in the northern region sell maize at home.

[6] This feature of the model is discussed extensively hereafter in the section dedicated to the storage option.

[7] Discounting is particularly relevant for farmers. Those who are more isolated are particularly afraid of missing opportunities to sell their products and may therefore be more impatient, displaying a discount factor that may converge toward zero.

and Nyanteng (2006) in studies of rural traders who make round trip journeys and must reach several deals to fill their truck. Although rural traders in the northern region can spend several days completing their trading trip, we opt for a one-day-trip scenario to facilitate the reading of the model. Because the road network is poorly developed, we assume that each trader returns by the same route on his way back, which leaves him the opportunity to stop again if needed. The bargaining then occurs in a succession of two sessions a day: one in the morning (period 1) and one in the afternoon (period 2). As is often reported in the literature, traders tend to dominate the interaction with farmers and are often said to dictate prices at the farmgate. In our model, we thus assume that the trader always begins the negotiation with a farmer by making an offer, which the farmer is bound to accept or to reject. This offer scheme applies for both bargaining sessions, and in the case where the farmer rejects the morning offer, the trader makes a new offer in the afternoon that the farmer can again either accept or reject.

Although a trader usually purchases from multiple farmers to fill his truck, we assume that each deal is made independently of other deals. In our model, the trader is impatient to complete his trading trip and makes offers accordingly. He makes a deal as soon as it is profitable, irrespective of whether he could make better deals with other farmers later. Indeed, because travel is costly due to poor road conditions and farmers' remoteness, filling a truck within a short time span is a priority.[8] Obviously, several farmers selling crops individually can present themselves simultaneously at the farmgate. However, we exclude an auction scenario in which a trader would offer the lowest possible price to a set of competing farmers. Moreover, although we do not exclude collective sales,[9] we make the assumption that farmers who are members of a group for marketing purpose can be considered as only one farmer, with a unique discount factor and a unique belief about the market price.[10]

In our framework, the trader is likely to get involved in a series of successive bargains, but he does not need to make the same offer to each farmer he meets. He makes customized offers, taking into account each farmer's impatience, his belief about the market price, and his transportation cost to reach the market. Although two farmers from the same community are likely to face similar transportation costs, they are also likely to face different liquidity constraints, meaning that they show different degrees of impatience when negotiating with the trader. Their beliefs about market prices may even differ because these beliefs are based not only on information they may get from fellow farmers but also on their personal experience as farmers.[11] Given the dispersion of farmers and the limited number of traders, a situation in which several traders would reach the same meeting point at the same time seems highly unlikely. However, several traders may visit the same community during the marketing season. This would allow farmers to reject some deals and wait for the next trader to come to get better deals. For the sake of clarity, we first discard this waiting option in our model, assuming that farmers are not patient enough to wait for the next trader to come. We relax this assumption thereafter.

We set the hypothesis about the information structure based not only on our own dataset but also on secondary data that stresses farmers' uncertainty about market prices. There are actually a number of sources of market information available to people; however, these sources usually fail to provide accurate, detailed, and timely price information.[12] In our data, the vast majority of farmers who did not participate

[8] According to the trader's truck, his location, and the season when the transaction occurs, one may assume that the trader has many opportunities to make deals, which may encourage him to focus on best deals only and skip the least profitable ones. Depending on how easy it is to reach a farmer, the trader's reservation price may increase. Technically, in our modeling framework, increasing the trader's reservation price would introduce a premium k in the utility function of the trader or to consider that m is the transportation cost of the trader plus this premium. This would not change our main results regarding the impact of an MIS.

[9] Note, however, that most of the farmers in our sample (85%) sell their products individually rather than collectively.

[10] We remain agnostic concerning the way in which the individual preferences and beliefs are aggregated into one group.

[11] Unavoidably, farmers get market price information indirectly from other farmer's bargaining sessions as farmers may share the prices they bargained for at the farmgate. However this only entails a revision of the farmer's belief about the market price before the negotiation starts, which does not affect the model. We thank an anonymous referee for pointing this out.

[12] In Ghana, the information gathered and collated by the Ministry of Food and Agriculture is distributed through periodic publications (weekly and monthly) and also through weekly radio broadcasts. However in our data, respondents almost never quote this source as their main information provider, although the proportion of farmers who own a radio is high (approximately 70%).

in the MIS program refer to fellow farmers, friends, and family as their main information providers. The information supplied to farmers through these informal sources is passed on mainly by word of mouth. Conversely, traders are able to gather updated information by traveling back and forth between marketplaces. Accordingly, we construct the model to reflect this asymmetry in information, assuming that traders are informed whereas farmers are not, unless they subscribe to the MIS. In the case where the farmer does not know the market price p^m, we assume that the farmer assigns a probability to types p^{m+} and p^{m-}. This probability is common knowledge, meaning that the trader is aware of it. We write ϕ_t to denote the probability assigned by the farmer that at period t market price is high and $1-\phi_t$ to denote the probability that market price is low. At period t, the farmer expects the market price to be $\phi_t p^{m+} + (1-\phi_t)p^{m-}$.

The Bargaining Game

We suppose that the bargaining between the two agents takes place in a finite sequence of two periods. This assumption is made without loss of generality, given that, in our setting, considering two periods allows for a complete characterization of the equilibrium set.[13] The game we examine is depicted in figure 1. At the time the two players meet at the farmgate, the market price can be high or low. In our framework, market price variability ($p^{m+} - p^{m-}$) does not refer to the intra-annual variability, which would be the difference between the postharvest period during which market prices are normally low and the lean season during which they are high. It refers instead to the interannual variability (i.e., the difference in prices from one year to another), which is much less predictable.

The trader starts the negotiation by making an offer in the morning. The farmer can then either accept or reject this offer. If he accepts, the two agents make a deal and the trader gives p_1 to the farmer for buying his product. If p_1 is insufficient, the farmer may reject the offer. By assumption, the farmer does not make a counteroffer, and rejection in the first period means that the bargain is postponed until the afternoon. Additionally, his utility will be discounted because he will not be able to reach the market immediately.[14] When the bargain is postponed, the utilities of the two agents are discounted according to their respective discount rates. When a second bargaining period occurs, the trader makes a new offer. Again the farmer can either accept or reject this offer. If the offer is accepted, the production is sold at price p_2. If the offer is rejected, the negotiation between the two agents ends, and the farmer then travels to the market himself. He incurs transportation cost c $(c > m)$ but sells his products at price p^m. The trader in this case seeks another seller.

If the farmer accepts p_1, the bargaining ends and the payoffs of agents are then, respectively, $U_T(p_1,1) = p^m - m - p_1$ and $U_F(p_1,1) = p_1 - s$. The trader never makes an offer such that $U_T(p_1,1) \leq 0$. If the farmer rejects the offer, he can either wait for the afternoon offer or go to the market by himself. In this last case, the farmer receives $U_F(p_1,1) = \delta_F[p^m - s - c]$. His utility is then discounted because he will be unable to reach the market immediately. Else, we assume the bargaining continues in the afternoon and the trader makes a new offer p_2. If agreement is reached in the afternoon, the payoffs to the agents are $U_T(p_2,2) = \delta_T[p^m - m - p_2]$ and $U_F(p_2,2) = \delta_F[p_2 - s]$. If bargaining ends in disagreement, payoffs are, respectively, $U_F(fail) = \delta_F[p^m - s - c]$ and $U_T(fail) = 0$. This is the worst possible outcome, and it implies that no agent has an incentive to intentionally seek disagreement.

The action set of the trader corresponds to all eligible offers making the deal profitable. We denote this by $\mathbb{F}_T$ which is the set of feasible prices the trader can offer, $\mathbb{F}_T \in]-\infty, p^m - m]$. A pure strategy for the trader consists of two actions $(p_1, p_2(.))$ where $p_1 \in \mathbb{F}_T$ is the first period offer and $p_2(.) \in \mathbb{F}_T$ is the second period offer, conditional on p_1 being rejected. The action set of the farmer is $\mathbb{F}_F\{a, r\}$, where a denotes acceptance and r

---

[13] Note that this is not the case in most bargaining games with incomplete information, where more periods involves more equilibriums. Multiplicity arises because perfect Bayesian equilibrium imposes no restrictions on players' beliefs following out-of-equilibrium moves. It follows that considering more periods translates into using more restrictive equilibrium notions, as in Sobel and Takahashi (1983) and Rubinstein (1985). In our setting, this is not the case because, as we shall see, there is no possible revision of the farmer's belief from one period to the other.

[14] Note that the negotiation may also end if the trader does not stop on his way back. In this case, the farmer will need to sell his products at the market himself. He will incur the additional cost c but he will benefit from a higher price p^m.

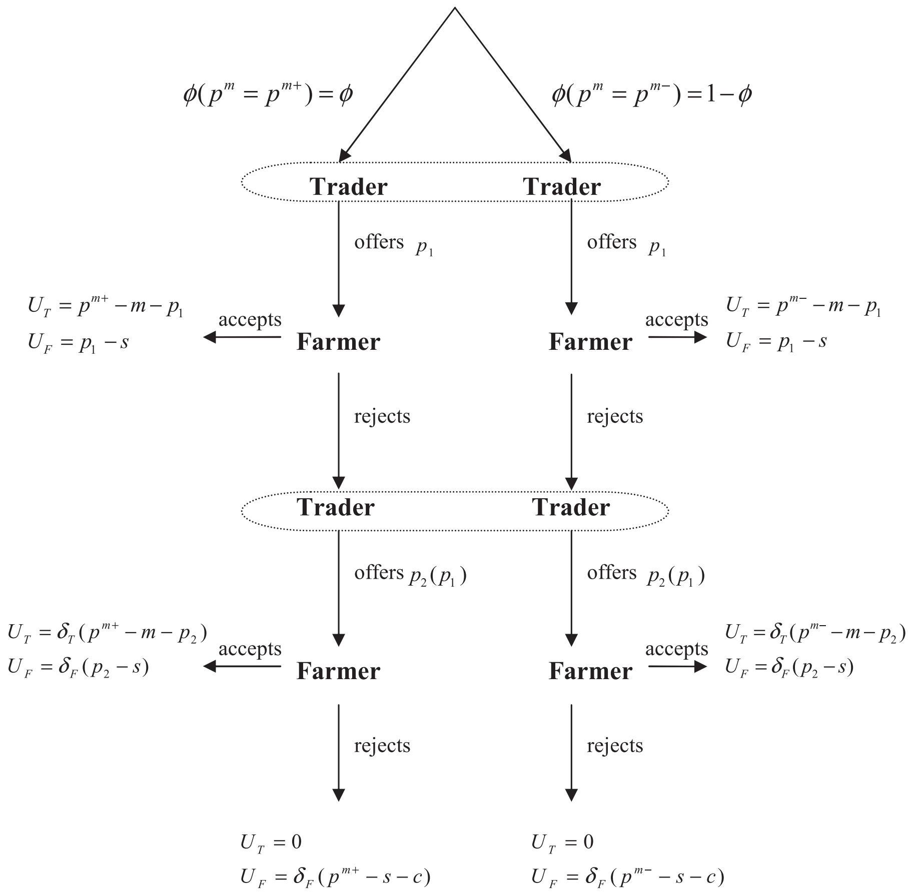

Figure 1. Diagram of the bargaining game

denotes rejection of the offer. A pure strategy for the farmer is a couple of actions $(F_1(.), F_2(.))$ where $F_1 \in \mathbb{F}_F$ is the best reply to the offer p_1 at the first period and $F_2 \in \mathbb{F}_F$ is the best reply to the offer p_2 at the second period, conditional on the offer being rejected in the first period.

How Does an MIS Affect Bargained Prices?

We answer this question by first considering the case where the farmer subscribes to an MIS. Both agents are perfectly informed, and this is common knowledge. For the sake of simplicity, we ignore the subscription fee and assume the service is free.[15] As usual, we solve the problem by backward induction. Focusing on the scenario in which a price p exists such that the reservation prices of the two agents are fulfilled, we have

(1) $$s \leq p \leq p^m - m.$$

The farmer's second period equilibrium strategy is easily computed. He accepts offer p_2 if and only if p_2 equals at least $p^m - c$. The trader therefore offers $p_2 = p^m - c$, which is accepted by the farmer. We then consider the strategy of the farmer in the first period. To maximize his utility, he should accept any offer p_1 such that $p_1 \geq \delta_F[p^m - c] + (1 - \delta_F)s$. The trader therefore offers

(2) $$p_1 = \delta_F[p^m - c] + (1 - \delta_F)s,$$

which the farmer accepts immediately. We deduce that when farmers are perfectly informed about the market price and when a profitable deal exists between the farmer and

[15] Note that this is actually the case in the data we collected.

the trader, there is a unique subgame perfect equilibrium:

Proposition 1. (Equilibrium with MIS). *Given the model parameters, a unique subgame perfect equilibrium exists: The trader offers* $p_1 = \delta_F[p^m - c] + (1 - \delta_F)s$ *and the farmer accepts it immediately.*

Solving the game with incomplete information involves the use of perfect Bayesian equilibrium. By definition, perfect Bayesian equilibrium requires that both agents play their best response given uncertainty, which means that the optimal choices depend on agents' beliefs. Given that the trader always offers a price lower than $p^m - m$, agreement is necessarily welfare improving for him. When information is incomplete, the farmer accepts offer p_2 if it is a best reply given the subjective probability ϕ. As shown by Ausubel, Cramton, and Deneckere, (2002) because the fully informed agent is making the offers, there is no possible revision of the probability distribution from one period to the other at the equilibrium ($\phi_1 = \phi_2 = \phi$). The trader is perfectly informed and, given ϕ, makes the minimal offer that is always accepted by the farmer: $p_2 = \phi p^{m+} + (1 - \phi)p^{m-} - c$. Accounting for price uncertainty, the farmer expects to get as well as he would if he went to the market himself. In other words, he is willing to let the trader capture the benefits corresponding to the gap between their respective transportation costs.[16]

The trader benefits from uncertainty when $p^m = p^{m+}$, but interestingly this is not the case when $p^m = p^{m-}$. This is because, when $p^m = p^{m-}$, the trader must compensate for the optimistic expectations of the farmer to secure a deal. Because the farmer believes the market price is high with a positive probability, he is willing to take the risk of going himself to the market if the trader's offer is too low. To avoid this situation, the trader concedes a share of his rent to the farmer. Although a Pareto improving agreement exists, the negotiation may still fail. To illustrate this, let us recall that if the deal fails, the trader gets a zero payoff from this transaction failure and seeks to make a deal with another farmer. Therefore, he is willing to offer $p_2 = \phi p^{m+} + (1 - \phi)p^{m-} - c$ if and only if the utility he receives is positive. We deduce that the trader makes offer p_2 if and only if

$$\phi(p^{m+} - p^{m-}) \leq c - m. \tag{3}$$

Else, he may make an offer such that $U_T \geq 0$, but this offer will be always rejected by the farmer. The two agents here end up in a worse situation. We deduce that uncertainty may collapse the agreement when $p^m = p^{m-}$ if the leeway between transportation costs is relatively small, if the probability ϕ is high, or if the price variability $p^{m+} - p^{m-}$ is high. In such cases, the farmer rejects any offer that could possibly be made by the trader because he expects to get a higher payoff by selling his products at the market himself. It follows that if $\phi(p^{m+} - p^{m-}) > c - m$, there is no offer made by the trader that the farmer accepts.

We now consider the strategy of both agents in the first period. If $\phi(p^{m+} - p^{m-}) \leq c - m$, meaning that if sufficient margins exist for the trader to secure a profitable deal, he always offers

$$p_1 = \delta_F[\phi p^{m+} + (1 - \phi)p^{m-} - c] + (1 - \delta_F)s. \tag{4}$$

The farmer always accepts this offer. Conversely, if $\phi(p^{m+} - p^{m-}) > c - m$, the farmer's belief and the market price variability are such that the differential of transportation costs between the two agents is too small for a deal to be mutually accepted. In this case, the trader either makes an offer that is always rejected by the farmer or he abandons the bargain and seeks another farmer. We deduce that in the bargaining game with incomplete information, there is a unique perfect Bayesian equilibrium:

Proposition 2. (Equilibrium without MIS). *Given the model parameters, a unique perfect Bayesian equilibrium exists: If* $\phi(p^{m+} - p^{m-}) > c - m$*, no profitable offer made by the trader can be accepted by the farmer; If* $\phi(p^{m+} - p^{m-}) \leq c - m$*, the trader offers* $p_1 = \delta_F[\phi p^{m+} + (1 - \phi)p^{m-} - c] + (1 - \delta_F)s$*, and the farmer accepts it immediately.*

[16] Although both the market price and the farmer's belief about the market price do not vary during the day, the trader's afternoon offer will not be the same as the morning offer: in the afternoon, he offers the price that the farmer would receive by selling at the market himself; in the morning, he offers the price that the farmer expects to receive by waiting for the afternoon offer.

Table 1. Bargaining Outcomes when Profitable Deals Exist

	Without MIS	With MIS	$f = p^1 - p^0$
$p^m = p^{m+}$	Deal	Deal	$f \geq 0$
$p^m = p^{m-}$ and $\phi(p^{m+} - p^{m-}) \leq c - m - k$	Deal	Deal	$f \leq 0$
$p^m = p^{m-}$ and $\phi(p^{m+} - p^{m-}) > c - m - k$	Failure	Deal	

Note: $p1$ (resp. $p0$) refers to the price offered by the trader when the farmer is informed (resp. uninformed).

The offer scheme is particularly important in producing these results because the sequentiality of periods cannot be used by the farmer to get information from the trader. In no case can the farmer strategically reject an offer to determine whether the market price is p^{m+} or p^{m-}. Note that allowing the farmer to make offers would give him more bargaining power and lead to another rent-sharing equilibrium.

Comparing equilibriums with and without subscription to MIS allows us to derive two principal insights. A first insight regards the impact of information on the occurrence of a deal failure (table 1). Although in our setting a Pareto improving deal always exists, asymmetric information about the market price may well lead the two agents to a negotiation failure. In this case, the trader gets a zero payoff, and the farmer goes to the market by his own means, ending up in a worse situation than the one he would have been in by accepting the deal. We deduce the following result:

Proposition 3. *MIS allows for avoiding a possible deal failure.*

When $\phi(p^{m+} - p^{m-}) > c - m$ and the market price is low, the uninformed farmer rejects any Pareto improving deal the trader can possibly offer. Subscribing to an MIS solves this inefficiency and ensures that any profitable deal will be achieved. Without MIS, a deal between the two agents is feasible if and only if $\phi(p^{m+} - p^{m-}) \leq c - m$. As soon as ϕ is larger than $\frac{c-m}{p^{m+}-p^{m-}}$, the trader is not able to make an offer that is profitable for himself as well as acceptable to the farmer. This deal failure is a consequence of the farmer's uncertainty about the market price. As soon as the transportation cost differential $c - m$ is not sufficient to compensate for the farmer's positive expectations about the market price, the agents end up with their outside option, which is the worst possible outcome for both of them. Inaccurate expectations about the market price will be all the more likely when interannual price variability is high, making information very valuable in environments where prices vary significantly from one year to another.

A second insight regards the impact of MIS over the prices bargained. For readability purposes, we call p^1 and p^0 the prices offered by the trader when the farmer is informed and uninformed, respectively (table 1). Focusing on the case where $\phi(p^{m+} - p^{m-}) \leq c - m$, which is the condition for reaching a deal despite price uncertainty, we know that if the farmer does not subscribe to an MIS, the trader offers $p^0 = \delta_F[\phi p^{m+} + (1 - \phi)p^{m-} - c] + (1 - \delta_F)s$. When the farmer subscribes to an MIS, the trader offers $p^1 = \delta_F[p^{m+} - c] + (1 - \delta_F)s$ if the market price is high and $p^1 = \delta_F[p^{m-} - c] + (1 - \delta_F)s$ if the market price is low. To make theoretical predictions about the impact of MIS on market prices, consider the mapping f such that $f = p^1 - p^0$. When market price is high, we have

$$f^+ = \delta_F(1 - \phi)(p^{m+} - p^{m-}), \tag{5}$$

and when market price is low, we have

$$f^- = -\delta_F \phi(p^{m+} - p^{m-}). \tag{6}$$

We deduce the following result:

Proposition 4. *A farmer's use of an MIS is beneficial when market price is high and detrimental when market price is low.*

An important insight is that interannual price variability is the key factor in determining whether an MIS has a positive or negative impact on the farmer. When market prices are high, the farmer benefits from obtaining information about market prices because it impedes the trader from taking advantage of the farmer's ignorance about the state of the market. The farmer assigns a positive probability of $(1 - \phi)$ to the low price occurrence, and the trader exploits this wrong expectation to capture an additional share f^+ of the surplus. The trader offers a price $p^0 < p^1$, and the farmer accepts this offer because he is not aware that he could obtain a higher utility by going to the market himself. This is the standard mechanism by which the trader is able to take advantage of the farmer's ignorance of market prices. When market price is low, price uncertainty works in the opposite way and allows for the farmer to capture an additional share f^- of the surplus. Because the farmer assigns a probability of ϕ to the high market price state, the trader has no other choice than to concede a share of his surplus to secure the deal.

The bigger the variability of prices $p^{m+} - p^{m-}$, the bigger $|f|$. If variability is high, a farmer's uncertainty about market prices is also high, making information even more beneficial when market price is high and detrimental when market price is low. Notice also that p^0 increases with ϕ. Said differently, when the probability assigned by the farmer gets closer to one, the farmer benefits less from price information. Finally, note that taking into account farmers' risk aversion in the model would lead to an higher (positive) impact of MIS. Incorporating a risk premium π into farmers' utility functions, as in Fafchamps and Minten (2012), translates in our setting as increasing the transportation cost of the uninformed farmer by this premium. Formally, it follows that adding risk aversion to our model does not affect p^1 but lowers p^0 such that $p^0 = \delta_F[\phi p^{m+} + (1-\phi)p^{m-} - c - \pi] + (1-\delta_F)s$. The direct consequence is that the positive impact of the MIS is larger in high-price years and may be positive in low-price years.

Discussion of Farmers' Storage Options

Up until now, we have assumed that the farmer is not patient enough to wait for another trader to visit him. It follows that his only outside option when the deal fails at the farmgate is to reach the market himself. However, as long as farmers are able to store grains and legumes at home, even in a suboptimal fashion, postponing the deal appears a reasonable option.[17] We thus wrote an extension to our model, in which the farmer has the opportunity to wait for another trader to visit him when the deal fails with the first trader. We argue in what follows that under some conditions, adding storage as an outside option in the model does not change our main results.

Data from the Ghana Living Standard Survey show that farmers in the northern region generally harvest maize between September and November and sell it between November and February, soon after the harvest and thus long before the lean season. We thus consider a finite game between one farmer and n identical traders in a sequence of n bargaining days over a fairly short time span. The bargaining game is depicted in figure 2. As in the original model, the farmer can either accept or reject the offer made by trader 1 in the morning. If he accepts, the bargaining ends. If the farmer rejects the morning offer, the bargaining continues in the afternoon and trader 1 makes a new offer. If the bargain ends in disagreement again, trader 1 seeks to reach a deal with another farmer, and his payoff in the bargain with the current farmer is null. On his side, the farmer either sells his products at the market or waits for the next trader to arrive. In this last case, a new bargain starts, similar to the previous one. Trader 2 trades as if no trader had previously visited the farmer.

How does an MIS affect bargained prices in this framework? Again we solve the game backward. Because the game we study is finite, if the farmer rejects the ultimate offer made by trader n, he should then go to the market himself. It follows that the farmer accepts the afternoon offer if and only if it equals at least the benefit he would get from going to the market himself. Given this, as in the original model, trader n makes a morning offer that equals at least the benefit the farmer would get by waiting for the afternoon, which the farmer accepts immediately. Similarly, because the farmer admits the outside option of going to the market himself at any time during the bargaining season, the two offers made by trader $n-1$ should be the same as those made by trader n. Indeed, both trader $n-1$ and the farmer know that trader n, if there is one, will not make an offer surpassing this outside option. Trader $n-1$ therefore makes offers to compensate the farmer for not going to the market by himself immediately. This applies to each previous bargaining session, and we deduce that the offers made by the set of n traders along the n days will always be

[17] We thank an anonymous referee for pointing this out.

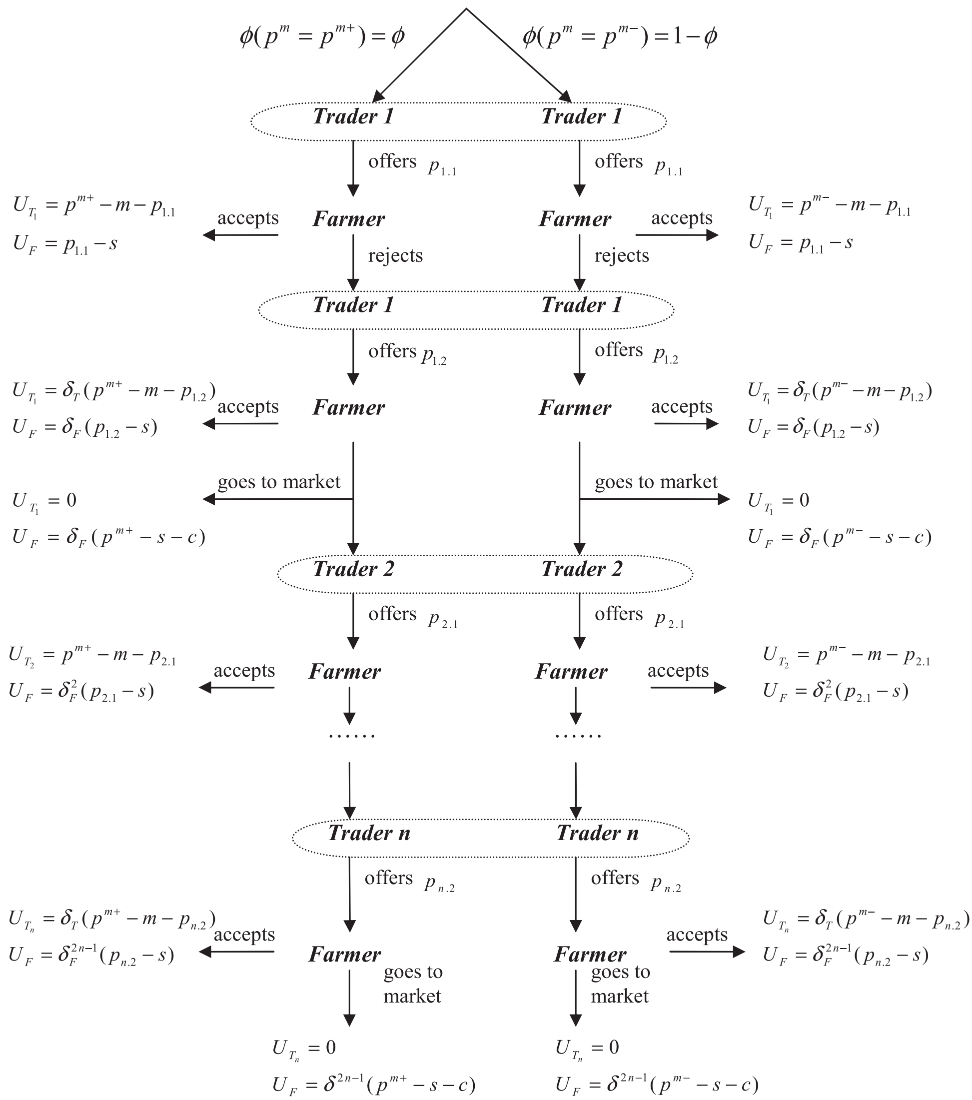

Figure 2. Diagram of the bargaining game with *n* traders

the same and will be computed on the basis of the best outside option available to the farmer, which is to go immediately to the market. We deduce that, when a profitable deal exists, the deal will be made immediately with the first trader because the farmer cannot expect to make a better deal with a later trader, which brings us back to the original model.

This result holds because in our framework the farmer does not make counteroffers and because we assume that the market price does not vary over the course of the n bargaining days. Indeed, as shown by figure 3, monthly maize prices in Tamale in the northern region appear remarkably stable between September 2009 and May 2010. Supposing that the market price increases, the new solution to the model would differ from the original solution because two factors would compete in the farmer's decision to go to the market rather than waiting. On the one hand, his impatience would encourage him to sell his production immediately, whereas on the other hand, the anticipated increase in market price during the lean season would encourage him to store his production and sell it later.

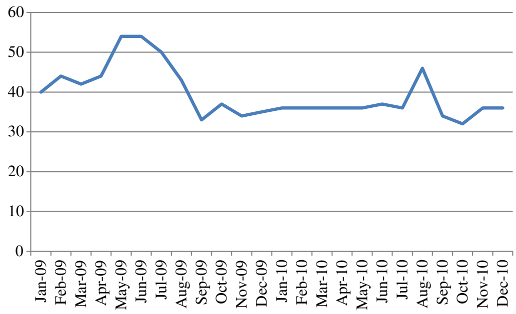

Figure 3. Retail prices of maize in Tamale during the period 2009–2010 (GHS/100 kg)

Source: FAO GIEWS Food Price Data and Analysis Tool (http://www.fao.org/giews/pricetool/).

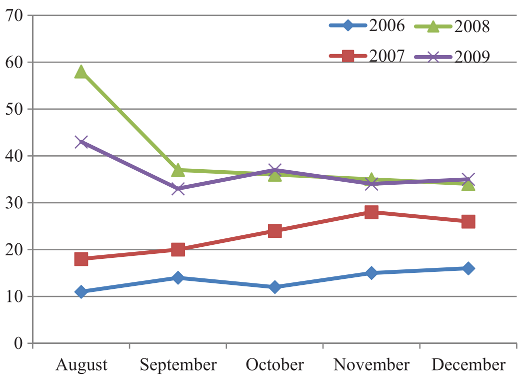

Figure 4. Retail prices of maize in Tamale (GHS/100 Kg)

Source: FAO GIEWS Food Price Data and Analysis Tool (http://www.fao.org/giews/pricetool/).

Empirical Framework

We test the model's prediction that information results in positive individual gain for the farmer using original survey data on farmers' marketing behavior in the northern region of Ghana in 2009, a high-price year as illustrated in figure 4. Specifically, we examine the causal effect of a program based on the MIS Esoko Program on farmgate prices.

The Program and the Data

Esoko (formerly TradeNet) began in 2005 with funding from USAID. Its main activity is to collect and provide market price information to subscribers by text messages. In practice, Esoko enumerators collect wholesale prices on local and distant markets and download them onto the platform so that, a few days later, subscribers receive price information on the most often quoted price for the products and the markets of their choice. Contrary to other price information providers, this customized service is designed to provide accurate, detailed, and timely price information twice a week. To promote their service, Esoko has worked with a partnering nongovernmental organization (NGO) called SEND West Africa since 2008. The NGO initiated the Eastern Corridor Agro-Information Center (ECAMIC) project by creating cooperative farmer groups within several communities in the northern Ghana districts. The northern region of Ghana covers approximately 30% of the country (Ministry of Food and Agriculture 2011). It is part of the agro-ecological zone called Guinea Savannah, where the wet season usually begins in April or May and ends in September or October, when the harvesting of the main season crops takes place. The total quantity of maize marketed annually in Ghana is reported to be approximately 1 million tons (USAID 2012). Maize is produced predominantly by smallholders who consume a significant share of it as a primary staple food (USAID 2012). Farmers sometimes intercrop maize with groundnuts.[18]

The ECAMIC program has been offered in thirty-six communities. It facilitated the acquisition of mobile phones by subsidizing cell phone purchases and paying for a one-year subscription to Esoko services. The program also included training on how to make sense out of the automatic price alerts. ECAMIC cooperatives generated lists of farmers who could be involved in the ECAMIC project. These eligible farmers must have been active members of the cooperative and must have owned an account at the credit union. Approximately two hundred farmers self-selected into the program in 2009. These first Esoko users began to receive SMS alerts on district market prices in June 2009. At the end of this year, SEND found another funder (Prestat Chocolate), which allowed them to expand the ECAMIC project. An additional wave of Esoko users were then trained and began to receive SMS alerts from Esoko in May 2010. The

[18] In the most densely populated parts of the zone, crop residues of legumes (especially groundnuts) are sold or traded for other goods (Karbo and Agyare 2002).

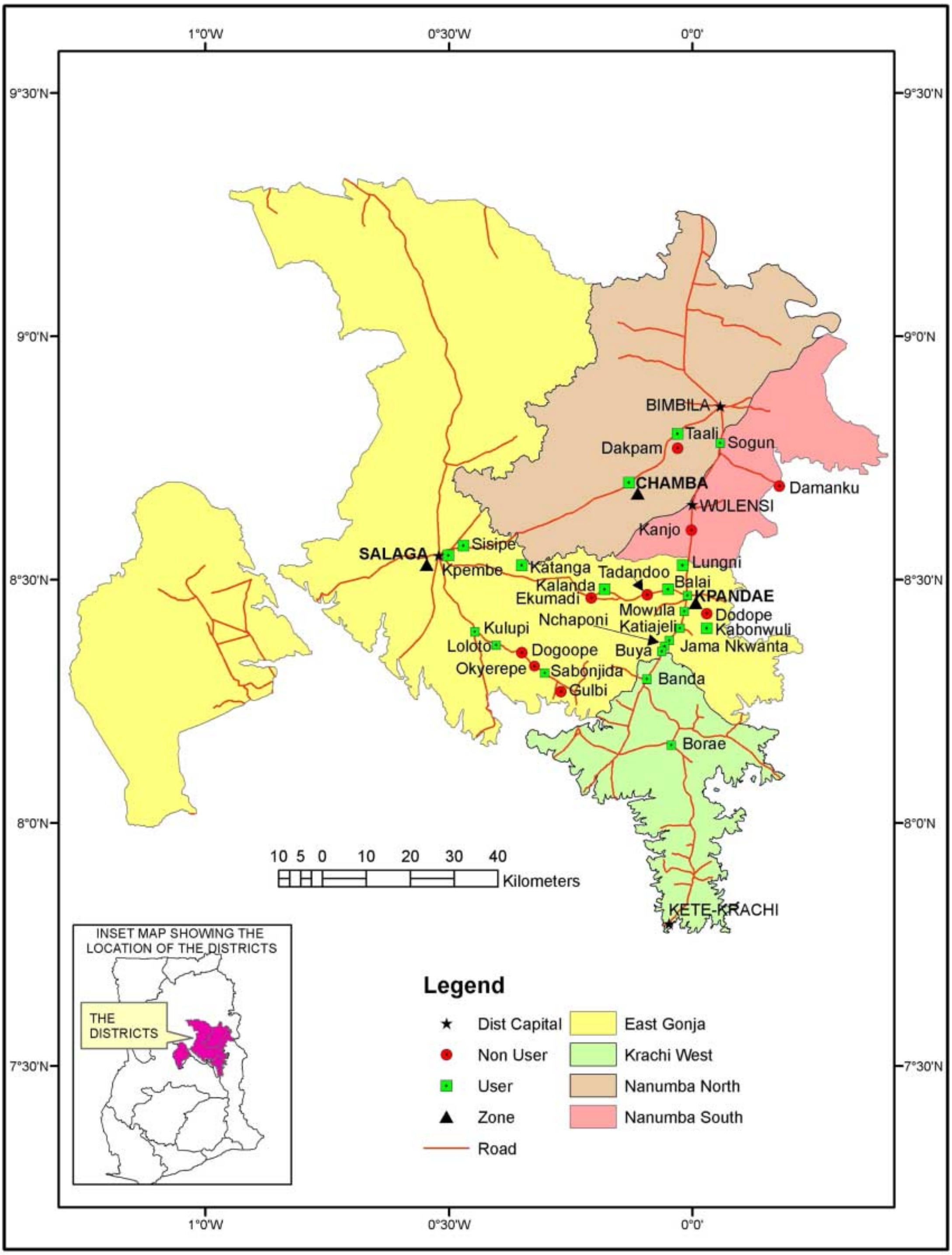

Figure 5. Location of surveyed farmers

first-wave participants enjoyed a fully subsidized subscription for a second time from the same date. The project ended in May 2011.

We surveyed six hundred farmers located in sixty-five communities, including the thirty-six communities that had been offered the

Esoko program (figure 5). We first surveyed all first-wave participants (a total of 196), obtained from the ECAMIC list of participants, as well as two hundred additional farmers living in ECAMIC communities. These latter farmers were randomly selected from the list of second-wave participants (two hundred out of three hundred). At the time we surveyed the second-wave participants (July 2010), they had recently been trained and set up for automatic SMS alerts on prices. Thus they had not had the opportunity to participate in the program during the 2009 marketing season. However, because of highly potential spillovers within communities, these nonparticipants residing in the same communities as first-wave ECAMIC farmers should be considered indirect users and therefore could not be used as a comparison group. To create a valid comparison group, we thus used observations from non-ECAMIC communities. Because the practical constraints of the project did not allow us to survey more than six hundred farmers in total, we surveyed two hundred additional farmers who, although they did not benefit from the ECAMIC project because they were not members of ECAMIC communities, lived in the same districts.

The sampling of the comparison group had specific features that are worth mentioning. First, because the entire population of non-users was quite large, we focused on composing our comparison group from communities that resembled the users' communities in several respects. First, those communities had to be roughly the same distance away from their nearest local market. Second, the percentage of literate farmers in the comparison group had to be the same as in the treated group (60%) because this is expected to facilitate the use of the service, although it does not generally require advanced skills. Third, to isolate the impact of Esoko from the impact of mobile phones alone, we included a screening question in our questionnaire so that enumerators in charge of untreated communities had to survey only farmers who had access to a mobile phone through their family.[19] In practice, once the villages have been selected on the basis of the geographical criteria, the enumerators went door-to-door in a random manner until they obtained the number of literate respondents with access to a mobile phone that had been set for each community.

Tables 2 and 3 describe information collected in the survey on the characteristics of the farmers and their main transaction for maize and groundnuts. The first point of sale occurs at the meeting point where all of the farmers from the local community meet the trader who visits the village.[20] Each farmer in the sample grows at least one crop of either maize or groundnuts. Table 2 reports mean values for various farmer characteristics. The cultivated area is 15 acres on average, with 5.8 acres of maize and 2.2 acres of groundnuts, which is similar to data from the Ghana Living Standards Survey. The average non-agricultural income is 600 Ghanaian cedi (GHS), although only half of the sample depends solely on agriculture for their income. We observe that the range of prices collected for maize and groundnuts (table 3) includes aggregate mean values provided by the FAOSTAT database (http://faostat.fao.org/) or calculated from the Ghana Living Standards Survey data: approximately 45 GHS for a maxi-bag (100 kg) of maize and 85 GHS for a maxi-bag of groundnuts. The quantity sold as a proportion of the total harvest quantity for each product is on average very large (68% for maize and 87% for groundnuts). The average distance to the nearest market is 15 km, and the average distance to the district market is 23 km.

Identification Strategy

Our parameter of interest is the average gain from the Esoko-based program for the subset of farmers who actually benefited from the program during the 2009–2010 marketing season. This parameter answers the following question: How much did informed farmers receive (in terms of a price premium) compared with what they would have received had they not entered the program? This is the so-called average treatment effect on the treated (ATT), defined as $ATT = E(p^1 - p^0 \mid w = 1)$, where p^1 denotes the farmer's outcome in the presence of the Esoko program (the treatment), p^0 denotes the outcome in the absence of the Esoko program, and w is a dummy that takes on the value of one

[19] In case those in Esoko communities had been provided with mobile phones whereas those in non-Esoko communities had not, it would have been impossible to know whether the estimated impacts are due to the MIS system or the mobile phone alone.

[20] Typically, the trader announces his arrival in the community by honking.

Table 2. Descriptive Statistics on Characteristics of Farmers (2008)

Variable	Unit	Obs	Mean	Median	Min	Max
Age	Years	596	41.3	40	17	85
Education	Yes = 1	599	0.6	1	0	1
Experience	Years	585	14.8	14	1	65
Nonagricultural income	GHS/year	599	608.3	0	0	16,400
Radio	Yes = 1	597	0.7	1	0	1
Cattle	Number	599	1.7	0	0	112
Goats	Number	599	3.6	1	0	40
Pigs	Number	599	1.6	0	0	40
Poultry	Number	599	12.2	10	0	50
Sheep	Number	599	1.5	1	0	39
Size of farmland	Acres	564	32.8	25	2	501
Cultivated area	Acres	534	14.7	12	1	112
Cassava area	Acres	587	3.0	1	0	110
Groundnut area	Acres	597	2.2	2	0	188
Maize area	Acres	596	5.8	2	0	70
Yam area	Acres	598	4.6	4	0	32
Total amount of credit received	GHS	599	205.4	70	0	5,000
Total amount of credit used for inputs	GHS	599	173.3	50	0	4,880
Purchase of fertilizer for groundnuts	GHS	599	29.0	0	0	1,000
Purchase of fertilizer for maize	GHS	599	104.8	30	0	4,000

Table 3. Descriptive Statistics on Characteristics of Main Transactions (2009)

Variable	Unit	Obs	Mean	Median	Min	Max
Sold maize as proportion of total harvested maize	Share	536	0.68	0.8	0	1
Sold groundnuts as proportion of total harvested groundnuts	Share	406	0.87	0.9	0	1
Price of maize (GHS/kg)	GHS	411	43.5	40.0	10	95
Price of groundnut (GHS/kg)	GHS	391	79.2	85.0	20	200
Collective sale	Yes = 1	586	0.14	0	0	1
Distance to community market	Km	570	15.4	13	0	64
Distance between community and district	Km	586	23.0	19	0	58

when the farmer is treated. We use matching methods to estimate the outcome level of the treated farmer in the unobserved state–namely, $E(p^0 \mid w = 1)$. The matching approach is widely used when evaluating development programs (Todd 2008). The main concerns in assessing the impact of development programs are related to the fact that such programs are not offered at random and that participants self-select into them. The crucial issue is thus to determine what factors are likely to drive both participation in the Esoko program as well as farmers' marketing performances. We did not find qualitative evidence suggesting that the NGO that supported the program had intentionally targeted farmers who marketed larger surpluses or lived in more isolated communities. Thus, we do not expect treated communities to differ from untreated ones on average. However, we can reasonably expect that farmers in treated communities who self-selected into the program systematically differ from nonparticipants. They presumably feel more comfortable using mobile phones and are relatively market-oriented farmers to begin with. Moreover, we know that the NGO had been working in this area for a long time, running various projects often involving the same communities. To the best of our knowledge, at least two NGO initiatives run in conjunction with the Esoko-based program can be considered confounding factors in our framework. First, participants in the Esoko-based program are also members of a credit union. Second, as members of the NGO, these farmers may also have opportunities to sell their products as a group.

Matching eliminates selection bias due to observable factors X by comparing treated farmers with observationally identical untreated ones (Imbens 2004). Because, even after conditioning on observable factors X, there may be systematic differences between informed and uninformed farmers' outcomes that could lead to a violation of the identification conditions required for matching, we choose to apply the difference-in-difference matching estimator, as defined in Heckman, Ichimura, and Todd (1997). This estimator allows for temporally invariant differences in outcomes between informed farmers and their X-matched uninformed counterparts because at least two observations per individual are available. It requires that $E(p_t^0 - p_{t'}^0 \mid X, w=1) = E(p_t^0 - p_{t'}^0 \mid X, w=0)$, meaning that the average difference in p between the two groups must be constant through time in the absence of treatment; in other words, that observationally identical treated and untreated individuals must exhibit the same change in p in the absence of treatment. Applied to our data, this identification strategy consists in comparing the annual change in the outcome of informed farmers with the annual change in the outcome of matched uninformed farmers. We measure annual change as the difference in farmgate prices between crop seasons 2008 and 2009.

Another key assumption for the validity of the difference-in-difference matching approach is that the treatment received by one farmer does not affect the outcome of another farmer. This assumption is referred to as the stable unit treatment value assumption in the statistics literature (Rubin 1978). In our framework, the validity of this assumption could be threatened in two ways. First, treated farmers may share Esoko price information with untreated farmers. Second, Esoko price information may have market equilibrium effects, affecting outcomes of both informed as well as uninformed farmers. Regarding the first issue, we do expect some information to diffuse between members of the same community, which is why we include the second-wave participants in the treated group as well. On the contrary, spillovers between communities are less likely because communities are somewhat geographically scattered, which may cause interactions and informal networks to be weaker across communities. Indeed, our data confirm that spillovers within communities are much larger than spillovers across communities: among two hundred non-users living with Esoko users in the same communities, 190 farmers stated that somebody they know had provided them price information that was obtained from their phone (in all cases, this information provider happened to be an Esoko user), whereas among two hundred nonusers living in different communities, albeit still in the neighborhood, only fifty-five farmers stated that they had benefited from such information (the information provider happened to be an Esoko user in thirty-eight cases out of fifty-five). We thus do not fear contamination in the control group because treated and untreated farmers live in separate communities. Regarding the market equilibrium issue, as long as informed farmers do not change the quantity that will be brought to the market (by the trader or by themselves), we should not expect market prices to be altered. We test this assumption in our data in the following section.

We use the nearest-neighbor matching estimator (Abadie et al. 2004), the kernel-based matching estimator, and the local linear matching estimator (Leuven and Sianesi 2003). The general form of the difference-in-difference matching estimator is

$$(7)\quad E(p^1 - p^0 \mid w=1) = \frac{1}{n_1} \sum_{i \in I_1 \cap S_P} (p_{it}^1 - p_{it'}^0 - E(p_{it}^0 - p_{it'}^0 \mid w=1, X_i))$$

with

$$(8)\quad E(p_{it}^0 - p_{it'}^0 \mid w=1, X_i) = \sum_{j \in I_0} \lambda_{ij}(p_{jt}^0 - p_{jt'}^0),$$

where I_1 denotes the group of treated farmers, I_0 denotes the group of untreated farmers, n_1 is the number of treated farmers in I_1. S_P denotes the common support, or the subset of treated farmers for whom the density of observationally identical untreated farmers is higher than some cut-off level (Todd 2008). Matching estimators differ in how matched untreated farmers are selected through the matching procedure. This difference is driven by the weights λ_{ij} that we assign to potential matches given their characteristics X. The nearest-neighbor matching estimator we use in the analysis matches each treated farmer to the closest untreated farmer or the four closest untreated farmers, according to the vector X. It is important that the covariables X are not affected by the treatment (Imbens 2004), which is why we use values from the pretreatment year 2008. We also apply the matching procedure to the summary statistic $Pr(w_i = 1 \mid X_i)$, the so-called propensity score (Rosenbaum and Rubin 1983).

We use the asymptotically consistent estimator of the variance of the nearest-neighbor matching estimator provided by Abadie and Imbens (2006), and we implement a bootstrap procedure (five hundred repetitions) to obtain an estimator of the variance of the kernel matching estimator and of the local linear matching estimator. We also control for the fact that observation units are grouped into clusters—namely the communities.

Another, computationally easier way to generate an estimate of the ATT is to regress w on y, controlling for X, by using ordinary least squares. However, in addition to the assumption of linearity, this requires us to assume that the gain associated with the program is constant across X, meaning that the impact of the program is the same for all informed farmers. Without any evidence for such an assertion, we thus opt for the widely used matching approach, which does not require specifying the functional form of the outcome equation and relaxes the assumption of constant additive treatment effects across individuals. We nevertheless run linear regressions as a robustness check.

Results

We present the results of the econometric analysis and provide a discussion on spillover effects and selection bias.

Impact of the Program on the Treated

We apply the matching procedure to the ECAMIC group of farmers (the treated group) and to the group of farmers who did not benefit from the ECAMIC project (the untreated group). As stressed before, ECAMIC farmers who entered the program after the marketing season under study cannot be considered part of the untreated group because of highly potential spillovers within treated communities. They are thus included in the treated group. Consequently our main estimates combine the direct effect on farmers receiving the information in 2009 and the indirect effect on their neighbors through information leakage.

Conditional probabilities for participation in the program are computed by estimating a probit model where the dependent variable is w and that includes all covariables X as regressors. We include in vector X the farmer's age, his level of education (a dummy that takes on the value of one if the farmer can read), his experience as a farmer (in years), the distance he lives from the nearest market (in kilometers), the total area of farmland (in acres), the area under cultivation for maize, cassava, groundnut, and yam (in acres), the number of livestock (cattle, goats, pigs, poultry, and sheep), whether or not he owns a radio, a motorbike, and/or a bicycle (dummies that takes on the value of one if yes and zero otherwise), the total value of his nonagricultural income (in GHS), and the size of his family (the number of adults and of children).

In addition, we control for what can be seen as confounding factors in our estimations. First, farmers who benefit from the program may also benefit from access to credit through the credit union. In the case where farmers use credit to buy inputs such as seed and fertilizers, they are more likely to produce higher yields. This may translate to larger transactions and consequently higher prices because the traders who travel to these farmers reduce transaction costs[21] and may consent to buy at a higher price. If this is true, without controlling for this potential credit union effect, our estimates would be biased upward. Moreover, farmers may also

[21] The traders who buy small quantities must bear the cost of sorting and grading each parcel to match it with parcels of similar quality goods. They may also have to weigh and repack the product and transport it to another market.

Table 4. Access to Credit

Credit Provider No. 1	ECAMIC	Prestat	Untreated	Total
No credit	28	29	94	151
Friend	8	8	18	34
Family	5	5	25	35
Trader	0	2	45	47
Credit union	129	109	7	245
Microfinance institution	19	20	0	39
SEND business program	2	0	0	2
Bank	5	30	11	46
Total	196	203	200	599

Table 5. Use of Credit

Credit 2008 No. 1	ECAMIC	Prestat	No-SEND	Total
No credit	28	29	94	151
Food	2	8	6	16
Livestock	1	3	3	7
Inputs	124	122	79	325
Equipment	32	27	16	75
Other	9	14	2	25
Total	196	203	200	599

Note: ECAMIC refers to the first-wave participants. Prestat refers to the second-wave participants. No-SEND refers to farmers who did not participate in the SEND program.

use credit to buy food or pay school fees. No longer under a liquidity constraint, they would be able to better negotiate prices in this scenario. If this is true, here again our estimates would be biased upward. Data suggest that only a small share of treated farmers declare not having access to credit (14%), contrary to untreated farmers (47%), as shown in table 4. Moreover, table 5 indicates that credit is mainly invested in inputs. We thus control for this potential credit union effect using additional covariables when running the matching procedure; namely, the total credit used for seeds and fertilizers (in GHS) and the harvest levels observed for maize and groundnuts in 2009. On the same note, we control for the trader as credit provider. As shown in table 4, almost no farmers from ECAMIC communities quote traders as credit providers, whereas more than 20% of untreated farmers do. By controlling with a dummy that takes on the value of one when the farmer benefits from trader credit, we ensure that only untreated farmers without trader credit can be matched to treated farmers.[22] Second, data also suggest that some treated farmers (20%) mainly sell their produce as a group, whereas untreated farmers almost never do. This may influence our estimates, again because the traders who travel to the farmers reduce their transaction costs when large quantities are available. We control for this potential collective marketing effect by adding into the set of covariables a dummy that takes on the value of one if the farmer usually sells crops in a collective way.[23]

The propensity scores are first used to define the common support (i.e., the subset of treated farmers for whom the density of untreated farmers with a similar propensity score is high enough).[24] The graph of the distribution of propensity scores suggests

[22] We thank an anonymous referee for pointing out the trader credit issue.

[23] Note that the variables we used to control for the potential effects of credit union membership and collective marketing are all choices of farmers. Yet, we believe that this does not create any bad control problem because, as for all other variables we use to correct for self-selection, we take their values before the unit being exposed to the treatment. Even the harvest levels observed in 2009 result from decisions made in 2008. We thus can safely assume that these variables are not likely to be affected by the treatment in 2009.

[24] To do so, we apply the standard procedure as described in Todd (2008): after excluding points for which the estimated density is zero, we exclude an additional small percentage of the remaining points for which the estimated density is positive but very low. Our estimated cut-off density is 0.078, and the trimming level is 0.007. The final number of treated farmers on the common support is 220 (out of 223).

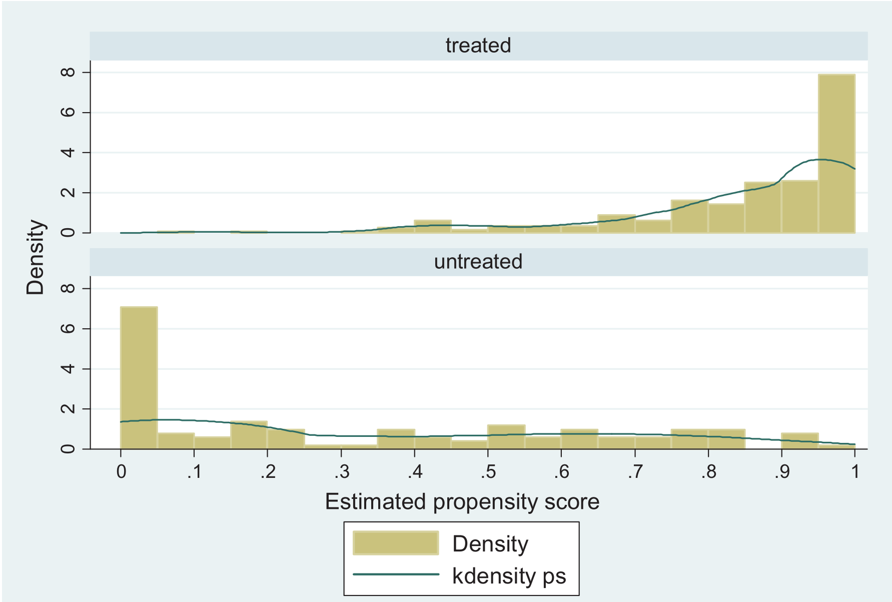

Figure 6. Propensity score distribution in the treated and untreated group

that densities are high enough for a wide range of propensity scores (figure 6). The matching procedure is considered successful when significant differences of covariables X among the treated and matched untreated are removed. We test the balancing property following the algorithm proposed by Becker and Ichino (2002) and conclude that it is satisfied.[25] We also compare the extent of balancing between the two groups before and after performing matching. Results show that the two groups did not differ much before matching, even for covariables for which we fail to reject the null of equality of means. Moreover, the matching procedure removed gaps that could be seen as important bias sources, such as distance to market, access to trader credit, or harvest levels (see balancing test in table 6).

Table 7 gives the estimated ATT in terms of price premium for both maize and groundnuts. Informed farmers received about 44 GHS for 100 kg of maize, which is 4.2 GHS more than the control group (taking the smallest significant matching estimator). They also received 76 GHS for 100 kg of groundnuts, approximately 5.2 GHS more than the controls. This means a 10.4% gain for maize and a 7.3% gain for groundnuts, compared with a situation without price information. Because it seems reasonable to examine the direct effect on farmers receiving the information in 2009, we also apply our identification strategy to the subset of first-wave ECAMIC farmers. Although focusing on direct users only considerably reduces the sample size, our estimates are still significant and similar to our main results overall, although slightly more scattered and sometimes not as precise (table 8).

The date at which the transaction takes place is an important determinant of the producer price because market prices are normally low soon after the harvest and high during the lean season. Unfortunately, our data do not indicate the month in which the transaction takes place. We thus cannot exclude the possibility that our sample includes some deals that occurred later in the season (for farmers who were able to store their product up to the lean season). If the treated farmers were able to store whereas the controls were not, the difference between marketing performances may only

[25] Becker and Ichino's algorithm splits the sample into k equally spaced intervals of the propensity score. Then within each interval, the algorithm tests that the average propensity score of the treated and control units does not differ. If the test fails in one interval, it splits the interval in half and tests again. In our analysis, the final number of blocks is six. This procedure ensures that the mean propensity score is the same for the treated and controls in each block. Results of the test indicate that all covariables are balanced except one (the cassava area).

Table 6. Balancing Tests before and after Matching

Variable		Mean		t Test		
		Treated	Control	*t*	*p* >| *t* |	
Age	Unmatched	42.77	39.99	1.75	0.08	
	Matched	42.77	42.10	0.65	0.52	
Education	Unmatched	0.62	0.57	0.72	0.47	
	Matched	0.62	0.62	−0.02	0.98	
Experience	Unmatched	15.36	12.92	2.26	0.03	*
	Matched	15.36	13.89	2.04	0.04	*
Nonagricultural income	Unmatched	521.38	889.87	−1.94	0.05	
	Matched	521.38	434.84	0.85	0.39	
Radio	Unmatched	0.78	0.75	0.55	0.58	
	Matched	0.78	0.70	1.80	0.07	
Adults	Unmatched	3.52	3.52	0.01	0.99	
	Matched	3.52	2.78	2.53	0.01	*
Children	Unmatched	3.64	3.19	1.34	0.18	
	Matched	3.64	3.38	1.14	0.26	
Motorbike	Unmatched	0.29	0.23	0.98	0.33	
	Matched	0.29	0.15	3.18	0.00	*
Bicycle	Unmatched	0.94	0.87	1.80	0.07	
	Matched	0.94	0.87	2.00	0.05	*
Cattle	Unmatched	2.04	3.64	−0.89	0.37	
	Matched	2.04	1.23	0.77	0.44	
Goats	Unmatched	3.49	3.27	0.30	0.77	
	Matched	3.49	3.14	0.70	0.49	
Pigs	Unmatched	1.18	1.31	−0.20	0.85	
	Matched	1.18	0.25	2.33	0.02	*
Poultry	Unmatched	11.68	11.48	0.15	0.88	
	Matched	11.68	13.13	−1.76	0.08	
Sheep	Unmatched	1.52	1.25	0.61	0.55	
	Matched	1.52	1.56	−0.12	0.90	
Cassava area	Unmatched	2.86	2.45	0.64	0.52	
	Matched	2.86	2.47	0.84	0.40	
Groundnut area	Unmatched	1.63	2.07	−2.16	0.03	*
	Matched	1.63	1.67	−0.25	0.80	
Maize area	Unmatched	4.90	5.56	−0.95	0.35	
	Matched	4.90	4.45	1.06	0.29	
Yam area	Unmatched	3.84	4.84	−2.36	0.02	*
	Matched	3.84	4.01	−0.61	0.54	
Distance to market	Unmatched	12.20	22.55	−7.30	0.00	*
	Matched	12.20	11.73	0.60	0.55	
Size of farmland	Unmatched	28.43	30.85	−0.79	0.43	
	Matched	28.43	29.58	−0.58	0.57	
Total amount of credit received	Unmatched	220.97	176.40	0.69	0.49	
	Matched	220.97	123.85	2.31	0.02	*
Trader credit	Unmatched	0.01	0.23	−6.90	0.00	*
	Matched	0.01	0.01	−0.05	0.96	
Purchase of fertilizer for groundnuts	Unmatched	33.60	33.08	0.08	0.94	
	Matched	33.60	34.98	−0.33	0.74	
Purchase of fertilizer for maize	Unmatched	117.21	112.96	0.10	0.92	
	Matched	117.21	104.55	0.45	0.65	
Price of maize sold	Unmatched	0.39	0.39	0.07	0.95	
	Matched	0.39	0.37	1.18	0.24	

Continued.

Table 6. Continued.

Variable		Mean		t Test		
		Treated	Control	t	$p>\|t\|$	
Total harvested maize	Unmatched	2659.70	2796.70	−0.23	0.82	
	Matched	2659.70	2389.10	0.70	0.49	
Total harvested groundnuts	Unmatched	491.89	667.83	−2.45	0.02	*
	Matched	491.89	443.29	1.07	0.29	
Collective sale	Unmatched	0.24	0.01	4.56	0.00	*
	Matched	0.24	0.12	3.00	0.00	*
Propensity score	Unmatched	0.86	0.39	15.49	0.00	*
	Matched	0.86	0.83	1.49	0.14	

Note: An asterisk denotes rejection of the null hypothesis (equality of means) at the 5% significance level.

reflect a systematic difference in their storage capacities rather than the impact of an MIS. However, there is a priori no reason that treated farmers store more than controls, except if they began storing because they had entered the Esoko program. In this case, storage could be seen as another outcome of the program: MIS users would be able to make better deals not only because they more effectively negotiate at the farmgate but also because they have the necessary information to engage in an optimal temporal arbitrage. Although we cannot exclude this potential effect, we doubt that it played a major role in farmers' marketing performances, given the magnitude of the impact we estimate. If treated farmers were able to store their product before entering the program, whereas the controls were not, this would result in a difference in prices between the treated and their matched counterparts in 2008, which we control for by applying the difference-in-difference matching estimator, supposing that the storage capacities that drive the gap in marketing performances between the two groups in 2008 did not vary over 2009 (the parallel trend assumption). Finally, even if storage capacities could be considered as time-varying sources of bias, the sensitivity test for matched data we applied indicates that selection bias is very unlikely in our data.

Table 7. Average Treatment Effect on the Treated

Estimator	Maize		Groundnut	
nnm_1_ps	4.19	**	6.21	**
	1.93		*3.06*	
nnm_1_x	5.78	***	7.26	**
	1.76		*3.08*	
nnm_4_ps	5.92	***	5.86	**
	1.34		*2.44*	
nnm_4_x	6.55	***	5.98	***
	1.22		*2.22*	
psm_kernel	5.27	***	5.20	*
	1.06		*2.97*	
psm_llr	5.29	*	8.56	
	3.02		8.16	
ols_ps	5.26	***	7.40	***
	1.48		*2.88*	
ols_x	4.70	***	5.37	***
	1.07		*2.04*	
n	260		206	

Note: Standard errors are in italics. Three asterisks denotes rejection of the null hypothesis (ATT = 0) at the 1% significance level, two asterisks denotes rejection of the null hypothesis at the 5% level, one asterisk denotes rejection of the nulll hypothesis at the 10% significance level. nnm is the nearest neighbor matching estimator, kernel is the kernel-based matching estimator, and llr the local linear matching estimator; x refers to the multivariable matching based on the distance between vectors X_i and X_j, and ps refers to univariable matching based on the distance between propensity scores. The number of matches used for nnm can be one or four. n is the sample size.

Discussion of Spillovers

According to the model, if the trader knew who was informed and who was not, he would naturally visit uninformed farmers when the market price is high and informed farmers when the market price is low. This would allow him to maximize his benefit and capture the highest possible share of the rent.[26] However, the Esoko program run in 2009 was the first Esoko-based program ever run. Therefore, traders could not have known that some farmers were MIS users before they met them. To the best of

[26] We thank an anonymous referee for pointing this out.

Table 8. Average Treatment Effect on the Direct Users

Estimator	Maize		Groundnut	
nnm_1_ps	3.93		6.32	**
	2.63		*2.88*	
nnm_1_x	*5.12*	**	5.29	*
	2.35		*3.11*	
nnm_4_ps	5.30	***	5.00	*
	1.78		*2.58*	
nnm_4_x	6.09	***	6.72	***
	1.62		*2.23*	
psm_kernel	4.99		11.58	***
	3.31		*2.45*	
psm_llr	17.98	***	7.50	
	5.93		*5.44*	
ols_ps	6.23	***	5.30	
	1.81		*3.33*	
ols_x	6.39	***	2.18	
	1.42		*2.35*	
n	129		119	

Note: Standard errors are in italics. Three asterisks denote rejection of the null hypothesis (ATT = 0) at the 1% significance level, two asterisks denote rejection of the null hypothesis at the 5% significance level, one asterisk denotes rejection of the nulll hypothesis at the 10% significance level. nnm is the nearest neighbor matching estimator, kernel is the kernel-based matching estimator, and llr the local linear matching estimator; x refers to the multivariable matching based on the distance between vectors X_i and X_j, and ps refers to univariable matching based on the distance between propensity scores. The number of matches used for nnm can be one or four. n is the sample size.

our knowledge, the mechanism by which an MIS is likely to alter the quantities sold by farmers has never been discussed theoretically. We however found one empirical study (Svensson and Yanagizawa-Drott 2010) that suggests that informed farmers may actually increase the share of output sold, compared with a situation without information. Such an impact may, in turn, alter the overall market price on the assembly market and thereby change the prices paid to farmers in uninformed communities. In light of our results, the theoretical explanation of this result could be that informed farmers would have an incentive to sell a higher share of their produce when the market price is high and a lower share when the market price is low, whereas uninformed farmers would be unable to adapt their supply to the variations of the market price because they do not know what it is. Such a quantity effect may alter the overall market price on the assembly market and thereby change the prices paid to farmers in the surrounding villages. The extent of this general equilibrium effect depends on how much farmers are able to increase the supply at the farmgate. We test this assumption in our data and fail to detect any significant change in the share of output sold by informed farmers (the interested reader can find the results of this test in a supplementary appendix online). We thus conclude that farmgate prices, not quantities sold, are altered by an MIS, which implies a transfer between traders and treated farmers that has no consequence in uninformed communities. This result accords with the fact that the farmers in our sample sold a very large share of their output in 2008 before the Esoko program starts and that we did not expect them to sell more thereafter.

To further discuss the spillover issue, we focus on farmers from ECAMIC communities only. We apply our identification strategy to the subset of direct users and compare them with their matched counterparts—nonparticipants living in ECAMIC communities as well. The results show no significant difference in the outcome between these two groups (see the supplementary appendix online), which indicates that the impact of an MIS program, if there is any, is the same on average in both groups.

Discussion of Selection Bias

We tackle the issue of selection bias by conducting a sensitivity analysis for our estimates. Although our empirical strategy is likely to perform well (because selection biases that are due to unobservable factors fixed through time are taken into account by the difference-in-difference methodology, whereas selection biases that are due to observable factors are taken into account through the matching procedure that is based on a large set of characteristics), there remains the possibility of a selection bias due to unobservable factors varying through time. We address this problem by using the bounding approach proposed by Rosenbaum (2002). This approach determines how strongly an unmeasured variable must influence the selection process in order to undermine the implications of the difference-in-difference matching analysis (Becker and Caliendo 2007). Two farmers with the same observed characteristics may differ in the odds of participating in the program by at most a factor of Γ. In a randomized experiment, randomization of the treatment ensures that $\Gamma = 1$. In an observational study, if $\Gamma = 2$ and two subjects are identical on matched covariables, then one might be twice as likely as the other to receive the treatment because they differ in terms of an unobserved covariable (Rosenbaum 2005). Although values of Γ are unknown, we try several values of Γ. This allows for identification of the critical levels of Γ at which the estimated ATT would become insignificant. The result of this test applied to our data indicates that the critical value for Γ is 3.6, which implies that farmers who have the same characteristics would have to differ in their odds of program participation by a factor of 3.6 (260%) to render the ATT insignificant. Even though unobservables may play a role, it is very unlikely that they would influence the odds of program participation to such a large extent. We are thus confident that our identification strategy performs well.

Conclusion

Although the potential for mobile-based MIS in agricultural development seems important, theoretical analyses of the conditions for its positive impact on farmers' marketing performances are rather scarce, as are empirical impact evaluations. First, we model bargaining interactions between a farmer and a trader, and we study how information affects the bargain and the balance of power at the farmgate. We elicit conditions for an MIS to improve farmers' marketing performances and demonstrate how information affects a farmer's decision to sell at the farmgate rather than at the market. An unexpected result of the model is that providing price information to the farmer allows him to avoid negotiation failures while Pareto improving deals exist. When deals do occur, the model shows that the impact of price information is positive when the market price is high and negative when the market price is low, an important finding given the high volatility of market prices from one year to the next.

Second, we use a quasi-experimental approach relying on survey data about farmers' transactions in northern Ghana in 2009, a high-price year compared with previous years. We estimate the causal effect of an MIS-based program on farmers' marketing performances and find that farmers who have access to the MIS received significantly higher prices for maize and groundnuts: approximately 10% more for maize and 7% more for groundnuts than what they would have received had they not participated in the program. These results suggest that the theoretical conditions for successful farmer use of MIS may be met in the field. However, it remains unclear whether a 10% gain in farmgate prices will be an incentive to adopt MIS technology. Indeed, despite the potential value of information and the low marginal cost of the technology (the cost of sending an SMS message), only a small share of African farmers actually use mobile-based MIS outside of development programs, for reasons that are not well documented.

Much remains to be done to test all of the predictions of the theoretical model. In particular, it would be useful to collect detailed data on transactions completed at the market due to negotiation failures at the farmgate. Indeed, the data we use only describe the main farmgate transactions, meaning that we are not able to estimate the average impact on informed farmers who travel to the market. Moreover, it would be interesting to investigate a more dynamic framework in which average treatment effects are not constant through time because of traders' strategy adjustments. In particular, we may suppose that if the diffusion of MIS is not uniform, meaning that MIS expands in some communities but not in others, traders may well adapt to this information landscape. Specifically, the trader should seek to deal in uninformed communities when the market price is high because, in that case, uninformed farmers, who systematically make incorrect estimates of the market price, would accept relatively low prices. On the contrary, the trader should seek to visit informed communities when the market price is low because it allows him to avoid costly negotiation failures.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/ online.

References

Abadie, A., D. Drukker, J.L. Herr, and G.W. Imbens. 2004. Implementing Matching Estimators for Average Treatment Effects in Stata. *Stata Journal* 4: 290–311.

Abadie, A., and G.W. Imbens. 2006. Large Sample Properties of Matching

Estimators for Average Treatment Effects. *Econometrica* 74: 235–67.

Aker, J.C. 2010. "nformation from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *American Economic Journal: Applied Economics* 2: 46–59.

Aker, J.C. and M. Fafchamps. 2013. Mobile Phone Coverage and Producer Markets: Evidence from West Africa. Working Paper, Centre for the Study of African Economies, University of Oxford.

Aker, J.C., and I.M. Mbiti. 2010. Mobile Phones and Economic Development in Africa. *Journal of Economic Perspectives* 24: 207–32.

Al-Hassan, R., A. Dorward, and C. Poulton. 1999. Improving Access to Maize Marketing Opportunities in Remote Areas of Ghana. Working Paper, University of Ghana Legon, Wye College.

Aryeetey, E., and V. Nyanteng. 2006. Agricultural Market Access in Ghana. Working Paper, Institute of Statistical, Social and Economic Research, University of Ghana Legon.

Ausubel, L.M., P. Cramton, and R.J. Deneckere. 2002. Bargaining with Incomplete Information. In *Handbook of Game Theory with Economic Applications*, vol. 3, ed. R. Aumann and S. Hart, 1897–1945. North-Holland: Elsevier.

Becker, S.O., and M. Caliendo. 2007. Sensitivity Analysis for Average Treatment Effects. *Stata Journal* 7: 71–83.

Becker, S.O., and A. Ichino. 2002. Estimation of Average Treatment Effects Based on Propensity Scores. *Stata Journal* 2: 358–77.

Bellemare, M.F., and C.B. Barrett. 2006. An Ordered Tobit Model of Market Participation: Evidence from Kenya and Ethiopia. *American Journal of Agricultural Economics* 88: 324–37.

Cole, S.A., and A.N. Fernando. 2012. The Value of Advice: Evidence from Mobile Phone–Based Agricultural Extension. Finance Working Paper 13-047, Harvard Business School.

Dorosh, P., H.G. Wang, L. You, and E. Schmidt. 2010. Crop Production and Road Connectivity in Sub-Saharan Africa: A Spatial Analysis. Policy Research Working Paper Series No. 5385, World Bank.

Fafchamps, M., and R.V. Hill. 2008. Price Transmission and Trader Entry in Domestic Commodity Markets. *Economic Development and Cultural Change* 56: 729–66.

———. 2005. Selling at the Farmgate or Traveling to Market. *American Journal of Agricultural Economics* 87: 717–34.

Fafchamps, M., and B. Minten. 2012. Impact of SMS-Based Agricultural Information on Indian Farmers. *World Bank Economic Review* 26: 383–414.

Goetz, S.J. 1992. A Selectivity Model of Household Food Marketing Behavior in Sub-Saharan Africa. *American Journal of Agricultural Economics* 74: 444–52.

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

Goyal, A., and C. González-Velosa. 2012. Improving Agricultural Productivity and Market Efficiency in Latin America and The Caribbean: How ICTs can Make a Difference? LCSSD Occasional Paper Series on Food Prices, World Bank.

Heckman, J.J., H. Ichimura, and P.E. Todd. 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies* 64: 605–54.

Imbens, G.W. 2004. Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *Review of Economics and Statistics* 86: 4–29.

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

Jensen, R.T. 2010. Information, Efficiency, and Welfare in Agricultural Markets. *Agricultural Economics* 41: 203–16.

Karbo, N., and W. Agyare. 2002. Crop-Livestock Systems in Northern Ghana. In *Improving Crop-Livestock Systems in the Dry Savannas of West and Central Africa*, ed. G. Tarawali and P. Hiernaux, 112–26 Nigeria: International Institute of Tropical Agriculture.

Key, N., E. Sadoulet, and A.D. Janvry. 2000. Transactions Costs and Agricultural Household Supply Response. *American Journal of Agricultural Economics* 82: 245–59.

Leuven, E., and B. Sianesi. 2003. PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. Statistical Software Components, Boston College Department of Economics.

Mérel, P.R., R.J. Sexton, and A. Suzuki. 2009. Optimal Investment in Transportation Infrastructure When Middlemen Have Market Power: A Developing-Country Analysis. *American Journal of Agricultural Economics* 91: 462–76.

Ministry of Food and Agriculture. 2011. Agriculture in Ghana: Facts and Figures 2010. Working Paper, Ministry of Food and Agriculture, Statistics, Research and Information Directorate.

Moschini, G., and D.A. Hennessy. 2001. Uncertainty, Risk Aversion, and Risk Management for Agricultural Producers. In *Handbook of Agricultural Economics* vol. 1, ed. B. L. Gardner and G. C. Rausser, 88–153. North-Holland: Elsevier.

Nakasone, E. 2013. The Role of Price Information in Agricultural Markets: Evidence from Rural Peru. Working Paper, AREC, University of Maryland, College Park.

Rosenbaum, P.R. 2002. *Observational Studies*, 2nd ed. New York: Springer-Verlag.

———. 2005. *Observational Study*, New-York: John Wiley & Sons.

Rosenbaum, P.R., and D.B. Rubin. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70: 41–55.

Rubin, D.B. 1978. Bayesian Inference for Causal Effects: The Role of Randomization. *Annals of Statistics* 6: 34–58.

Rubinstein, A. 1985. *Choice of Conjectures in a BargainingGgame with Incomplete Information*. Cambridge, UK: Cambridge University Press.

Sobel, J., and I. Takahashi. 1983. A Multistage Model of Bargaining. *Review of Economic Studies* 50: 411–26.

Svensson, J., and D. Yanagizawa. 2009. Getting Prices Right: The Impact of the Market Information Service in Uganda. *Journal of the European Economic Association* 7: 435–45.

Svensson, J., and D. Yanagizawa-Drott. 2010. Tuning in the Market Signal: The Impact of Market Price Information on Agricultural Outcomes. Working Paper. Institute for International Economic Studies. Stockholm University.

Teravaninthorn, S., and G. Raballand. 2009. Transport Prices and Costs in Africa: A Review of the Main International Corridors. Working Paper, International Bank for Reconstruction and Development/World Bank.

Todd, P.E. 2008. Evaluating Social Programs with Endogenous Program Placement and Selection of the Treated. In *Handbook of Development Economics.* vol. 4, 1st ed. T. Paul Schultz and John A. Strauss, 3847–94. North-Holland: Elsevier.

United States Agency for International Development [USAID]. 2012. The Market for Maize, Rice, Soy, and Warehousing in Northern Ghana. Working Paper, USAID.

———. 2010. Using ICT to Provide Agriculture Market Price Information in Africa. Working Paper, Fostering Agriculture Competitiveness Employing Information Communication Technologies, USAID.

World Bank. 2009. Eastern Africa: A Study of the Regional Maize Market and Marketing Costs. Working Paper, International Bank for Reconstruction and Development/World Bank.

Copyright of American Journal of Agricultural Economics is the property of Oxford University Press / USA and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.