Mobile Phone Coverage and Producer Markets: Evidence from West Africa

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Mobile phone coverage has expanded considerably throughout the developing world, particularly within sub-Saharan Africa. Existing evidence suggests that increased access to information technology has improved agricultural market efficiency for consumer markets and certain commodities, but there is less evidence of its impact on producer markets. Building on the work of Aker (2010), we estimate the impact of mobile phone coverage on producer price dispersion for three commodities in Niger. Our results suggest that mobile phone coverage reduces spatial producer price dispersion by 6 percent for cowpea, a semi-perishable commodity. These effects are strongest for remote markets and during certain periods of the year. The introduction of mobile phone coverage has no effect on producer price dispersion for millet and sorghum, two staple grains that are less perishable and are commonly stored by farmers. There are no impacts of mobile phone coverage on traders' gross margins or producer price levels, but mobile phone coverage is associated with a reduction in the intra-annual price variation for cowpea. These results are potentially explained by increased inter-temporal arbitrage by farmers for storable commodities such as millet and sorghum.

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Introduction

Price information plays an important role in arbitrage behavior and market efficiency. Access to such information has improved significantly in developed countries, especially with the introduction of online databases (Autor 2001; Anderson and Magruder 2012). In sub-Saharan Africa, long distances and limited infrastructure have historically made obtaining such information costly. The spread of mobile phone coverage over the past decade has significantly reduced the costs of obtaining such information, thereby enabling consumers, traders, and producers to send and receive information more quickly and cheaply (Aker and Mbiti 2010). Although a growing body of evidence suggests that this increased access to information has improved consumer market efficiency, there is more limited evidence on its impact on producer markets, which form an important segment of the population.

Between 2001 and 2008, mobile phone networks were introduced in Niger, with more than 44 percent of the population having access to mobile phone service by 2008 (Aker 2010; authors' calculations from GSMA). By 2008, 90 percent of agricultural markets in our sample had mobile phone coverage. Although coverage in 2008 remained relatively limited in rural villages, the introduction of mobile phones reduced farmers' and traders' costs of obtaining market information (Aker 2010), since 55 percent of farmers transport their output to local markets to sell (author's calculations).

This paper estimates the impact of mobile phone coverage on the spatial producer price dispersion for three commodities in Niger. We first develop a simple model explaining how the circulation of information among traders is likely to improve spatial arbitrage for producer markets. The model shows that the improved circulation of information about local market conditions reduces spatial producer price dispersion because it allows traders to engage in spatial arbitrage. These effects should be strongest for perishable and semi-perishable commodities when inter-temporal arbitrage is absent. However, theoretical predictions related to producers' prices and traders' gross margins are ambiguous because they depend on the market structure and relative elasticities of supply and demand for a particular commodity.

We test these theoretical predictions using market-level panel data on producer prices for millet, sorghum, and cowpea in Niger. Using a difference-in-differences estimation strategy similar to that employed in Aker (2010), we find that mobile phone coverage reduced the spatial dispersion of producer prices by 6 percent for cowpea, a semi-perishable cash crop in Niger. These effects are larger for more isolated and surplus markets and during certain periods of the year. We find no effect of mobile phone coverage on producer price dispersion for millet or sorghum or on gross margins or producer price levels. Nevertheless, mobile phone coverage reduced intra-annual producer price variation for cowpea by 6 percent.

To understand the mechanisms behind these results, we use farmer-level data to better understand the correlations between mobile phone coverage and farmers' marketing behavior. Tack and Aker (2014) find evidence that mobile phone coverage increased traders' search behavior, with stronger effects over time. Our results suggest that mobile phone ownership is associated with farmers' improved access to market information but that this does not affect farmers' marketing behavior or sales prices. These results are consistent with those of Fafchamps and Minten (2012) and Aker and Ksoll (2013).

Our paper makes two contributions. First, the results contribute to a substantial economic literature showing that information is crucial for the effective functioning of markets, both from a theoretical (Stigler 1961; Reinganum 1979; Stahl 1989) and an empirical perspective (Autor 2001; Brown and Goolsbee 2002; Jensen 2007; Aker 2010; Goyal 2010). Most of this work has focused primarily on consumer markets, with a more recent extension to producer prices (Muto and Yamano 2009; Goyal 2010; Fafchamps and Minten 2012). However, few of these studies assess the impact of information technology on producer price dispersion and prices, as our work does.

Second, much of the existing literature concentrates on the impact of information technology on a single good (Jensen 2007; Aker 2010; Goyal 2010). To our knowledge, only Muto and Yamano (2009) and Nakasone (2013) assess the relative impact of information technology on perishable and non-perishable commodities. Our study is able to consider the impact of information technology on multiple goods with varying perishability and over a long time period.

The rest of this paper proceeds as follows. Section 1 provides an overview of the context and research design. Section 2 presents the theoretical framework. In Section 3, we present our data, and Section 4 discusses the empirical strategy. Section 5 provides the main empirical results. Section 6 concludes.

Context

With a per capita Gross Domestic Product (GDP) of US$330 and an estimated 61 percent of the population living in extreme poverty, Niger is one of the lowest-ranked countries on the United Nations Human Development Index (United Nations Development Program 2013). Agriculture employs more than 80 percent of the total population and contributes approximately 40 percent to the GDP (World Bank 2010). The majority of the population consists of subsistence farmers who depend on rain-fed agriculture and livestock as their main sources of income.

Subsistence farmers primarily cultivate millet, sorghum, and cowpea with a unimodal rainfall system. Although these commodities can, in principle, be stored for several years, a majority of the farmers and traders in our study area store for shorter periods and rarely engage in inter-annual storage (Aker 2008; Tack and Aker 2014).[1] Cowpea, in particular, is highly susceptible to storage insects (the cowpea weevil), with storage losses estimated to be 25 percent (Jackai and Daoust 1986). As a result, cowpea is often considered a semi-perishable commodity (Murdock et al. 1997).

Although a majority of farmers in our sample are net consumers, they often sell a portion of their production at some point in the year. All three commodities are traded through a system of weekly agricultural markets (Aker 2010). Farmers typically sell their agricultural products to smaller traders (e.g., retailers and intermediaries) located within their village or at a nearby weekly market (an average of 7.5 km away). These smaller traders sell to wholesalers and semi-wholesalers in local markets, who, in turn, sell to buyers (wholesalers, retailers, or consumers) in regional markets. Although an agricultural market information system has existed in Niger since the 1990s, 89 percent of traders and 75 percent of farmers state that they primarily obtain price information through personal networks (Aker 2010).[2]

Mobile phone service was introduced in Niger in October 2001 (Aker 2010). Three private mobile phone operators (Celtel, Sahelcom, and Telecel) intended to provide universal coverage by 2009, with mobile phone service rolled out in different markets over time. At the outset, mobile phone operators prioritized urban centers and proximity to international borders.[3] As a result, the capital city and regional capitals received coverage during the first three years of mobile phone rollout, followed by a quasi-random pattern in later years.

Figure 1 shows the spatial rollout of mobile phone coverage by market and by year between 2001 and 2008. Mobile phone coverage increased substantially during this time, with 44 percent of the population and 90 percent of the weekly markets having access to mobile phone service by 2008. The greatest increase in mobile coverage into more remote rural areas occurred between 2008 and 2010, after our study period.

Although landlines existed prior to 2001, Niger has the second-lowest landline coverage in the world, with only two landlines available per 1,000 people (World Bank 2006). The number of landlines remained relatively stable during this period (Figure 2).[4] Among all of the agricultural markets in our study, only one received new landline coverage between 1999 and 2008.

Despite a large increase in mobile phone coverage, Niger had the lowest adoption rate in Africa in 2008. There were an estimated 1.7 million mobile phone subscribers, representing 12 percent of the population (authors' calculations from Wireless Intelligence). A trader survey conducted in 2006 showed that 31 percent owned a mobile phone and used it for their trading operations (Tack and Aker 2014). In contrast, less than 5 percent of farm households owned a mobile phone at that time.[5]

Conceptual Framework

To clarify the way in which we expect mobile phone coverage to affect producer price dispersion, we present a model of agricultural markets visited by farmers and itinerant traders. The model is based on a fair but stylized description of how agricultural traders operate in sub-Saharan Africa (Fafchamps, Gabre-Madhin, and Minten 2005).[6]

Because each market operates for a limited duration on different days and because markets are often far apart, it is difficult for farmers or traders to visit more than one market in a given day. In the absence of limited communication devices, farmers and traders must visit a market to obtain price information and are limited to one per day. For Nigerien farmers, these travel costs are substantial because the average distance to the nearest market is 7.4 km, or 1.5 hours.[7] For this reason, farmers often sell their output in the village (farm-gate) or at the closest market and are reluctant to transport their output home because of transport costs. As a result, supply on any given market day is inelastic. Because each weekly market serves a large geographic area, farmers cannot coordinate supply. Consequently, supply varies randomly across market days in ways that traders cannot easily predict. If better-informed traders can select which market to visit depending upon local supply, this situation would generate a potential gain from spatial arbitrage.

The introduction of mobile phone coverage in Niger reduced the cost of obtaining information in general and particularly for information about local market conditions. Aker (2010) estimated that the cost of obtaining price information from a market located 10 km away decreased by 35-50 percent with the introduction of mobile phone coverage.[8] This cost reduction had a greater effect on traders (compared with farmers) because traders were more likely to adopt mobile phones and operated in different weekly markets, which had mobile phone coverage. In contrast, mobile phone coverage did not expand significantly into more remote rural villages, farmers' primary residence, until after 2008.

Our model captures these different features to illustrate how mobile phone coverage can increase spatial arbitrage and reduce price dispersion while keeping the average producer price unaffected.

The Model

To provide a focus, we consider a static, symmetric, one-period model without intertemporal arbitrage. Each risk-neutral trader has n markets nearby, all located at the same distance d with transport cost c.[9] Each market is reachable by n traders, and each trader has a working capital of k. In the morning, the trader visits a single market, m, and purchases all possible quantities with working capital k at the going price p_m. In the afternoon, the trader sells the total quantity purchased to his home market.

In the morning of day *t,* producers bring a random quantity of agricultural goods $\tilde{q}_m$ to market *m.* The distribution *F(q)* of $\tilde{q}_m$ is the same in all markets and is known to traders, but the exact quantity in each market is unknown.[10] Let $E[\tilde{q}_m] = \bar{q}$ for all m. Each morning, a trader must select a market *m* among the *n* markets that he could potentially visit.[11] Let $\tilde{d}_m$ be the number of traders who happen to choose market *m* on a particular day *t*. Because traders randomize equally among all *n* markets, $\tilde{d}_m \sim B(1, \frac{n-1}{n})$, it follows that the variance of $\tilde{d}_m$ increases in *n,* the number of markets from which the traders must choose.

The total demand is equivalent to $\tilde{d}_m k$, the number of traders multiplied by their individual working capital. The price in market *m* on a given day *t* is given by the standard supply equals demand equilibrium:

(1) $$p_m \tilde{q}_m = k\tilde{d}_m.$$

Setting $k = 1$ by choice of units, this reduces to $p_m = \frac{\tilde{d}_m}{\tilde{q}_m}$. In other words, the price on a given market *n* on a given day *t* is the same for all farmers and traders in that market, but there is spatial price variation across markets. For a given distribution *F*(*q*), the variance of p_m is increasing in the variance of d_m and hence *n*. The quantity that each trader *i* purchases on a given day is

(2) $$\tilde{q}_i = \frac{\tilde{q}_m}{\tilde{d}_m},$$

which is increasing in the number of farmers who brought their output to the market that day and decreasing in the number of traders who chose market *n*.

In the absence of temporal arbitrage, a trader must sell in his/her home market. We assume, for simplicity, that each trader sets the sales price to cover transport costs plus a unit profit margin *r*. The sales price for trader *i* is thus

(3) $$\tilde{p}_i = \tilde{p}_m + c + r.$$

Because the profit of trader *i* is $r\tilde{q}_i$, the trader would prefer to buy from markets with many farmers (i.e., a high $\tilde{q}_m$) and few other traders (i.e., a low $\tilde{d}_m$). In other words, a trader could benefit from obtaining an informative signal about the realization of $\tilde{q}_m$ or $\tilde{d}_m$. Without this signal, the trader's best response function is

(4) $$max_{p_m} \sum_{m=1}^{n} \pi_m r E[\frac{\tilde{q}_m}{1+\hat{d}_m}] ,$$

where π_m is the probability that trader *i* will visit market *m* and $\hat{d}_m$ is the number of traders other than trader *i* in market *m*. In a symmetric equilibrium, $\tilde{d}_m$ is not correlated with $\tilde{q}_m$ because traders do not know $\tilde{q}_m$ and all markets have the same ex ante *F*(*q*). The best response function can therefore be rewritten as

(5) $$max_{\pi_m} r\bar{q} \sum_{m=1}^{n} \pi_m E[\frac{1}{1+\hat{d}_m}],$$

where $\hat{\pi}_m$ is the probability that the other *n*-1 traders visit market *m*. The distribution function for $\hat{d}_m$ is

(6) $$\Pr(\hat{d}_m = x) = \binom{n-1}{x}(\hat{\pi}_m)^x(1-\hat{\pi}_m)^{n-x-1}.$$

Given symmetry, it follows that $\pi_m = \hat{\pi}_m = \frac{1}{n}$, i.e., that each trader randomizes equally across the *n* markets. Without information on $\tilde{q}_m$ or $\tilde{d}_m$, all markets are ex ante equivalent from the point of view of traders.

Informative Signals

Let us now assume that trader *i* receives a costless (private) informative signal *s*, such as a phone call, about the number of farmers $\tilde{q}_m$ and learns that $E[\tilde{q}_m|s] \gg E[\tilde{q}_m]$. Signal *s* breaks the symmetry between markets for trader *i,* whose best response function becomes

(7) $$max_{\pi_s} \pi_s r E\left[\frac{\tilde{q}_s}{1+\hat{d}_s}\middle|s\right] + \sum_{m=1}^{n-1} \frac{1-\pi_s}{n-1} r E[\frac{\tilde{q}_m}{1+\hat{d}_m}],$$

where π_s is the probability of trader *i* visiting markets with a signal and $\pi_m = \frac{1-\pi_s}{n-1}$ is the probability of trader *i* visiting markets without a signal. If other traders do not receive the private signal, then $F(\hat{d}_s) = F(\hat{d}_m)$. Hence, $\hat{d}_s$ is independent of the realized $\tilde{q}_s$ and *s*. If $\bar{q}_s \equiv E[\tilde{q}_s|s]$ and we assume that $\bar{q}_s > \bar{q}$, then equation (7) can be rewritten as

(8) $$max_{\pi_s} r\bar{q}_s\bar{C}\pi_s + r\bar{q}\bar{C} \sum_{m=1}^{n-1} \frac{1-\pi_s}{n-1} = r\bar{q}_s\bar{C}\pi_s + r\bar{q}\bar{C}(1-\pi_s),$$

where $\bar{C} \equiv E[\frac{1}{1+\hat{d}_m}]$ denotes the competition that trader i expects to face on market m. Solving the first-order conditions (FOC) yields the following:

$$r\bar{q}_s\bar{C} = r\bar{q}\bar{C}, s.t. \bar{q}_s = \bar{q}\ , \tag{9}$$

which shows that if the signal is informative, playing a randomized strategy is no longer optimal. The informed trader then sets

$$\pi_s = 1\ if\ \bar{q}_s > \bar{q} \text{ and } \pi_s = 0\ if\ \bar{q}_s < \bar{q}. \tag{10}$$

In other words, if the signal is informative and the other i-1 traders remain uninformed, trader i is no longer indifferent between all n markets but visits market m with probability 1 if $\bar{q}_s > \bar{q}$. All else equal, the informative signal s reduces price dispersion across markets. The informed trader buys from a large surplus market, thereby increasing the price in that market, and abandons a small surplus market, thereby reducing demand and prices there. Thus, the action of the informed trader reduces the price difference between high and low surplus markets.

A similar outcome is obtained if all traders receive the same signal s. To solve for the mixed strategy analytically, we assume that traders are divided into non-overlapping geographical areas consisting of one consumer market and n supply markets. We now have $F(\hat{d}_s) \neq F(\hat{d}_m)$. If $\frac{\bar{q}_s}{n} = \bar{q}\bar{C}$, the signal in favor of market s is very strong, and there is a corner equilibrium: all n traders go to market s and do not visit the other markets on that day, which is the pure strategy equilibrium case. If, however, the signal is not strong, traders are not all attracted by the same market, and there is a mixed strategy equilibrium in which each trader's best response is

$$max_{\pi_s} \pi_s r\bar{q}_s E\left[\frac{1}{1+\hat{d}_s}\middle|s\right] + (1-\pi_s)\bar{q}rE[\frac{1}{1+\hat{d}_i}], \tag{11}$$

where $\hat{d}_i$ denotes the number of traders in markets other than s. In general, $\hat{d}_i \neq \hat{d}_m$. The condition for an interior solution is that

$$\theta \equiv \bar{q}_s/\bar{q} = E\left[\frac{1}{1+\hat{d}_i}\right]/E\left[\frac{1}{1+\hat{d}_s}\middle|s\right]\ , \tag{12}$$

where θ represents the strength of the signal.

By symmetry, all traders face the same decision problem. Thus, their π_s will all be the same:

(13) $$\Pr(\hat{d}_s = x) = \binom{n-1}{x}(\pi_s)^x(1-\pi_s)^{n-x-1}$$

(14) $$\Pr(\hat{d}_i = x) = \binom{n-1}{x}\left(\frac{1-\pi_s}{n-1}\right)^x\left(1-\frac{1-\pi_s}{n-1}\right)^{n-x-1}.$$

The system of three equations (12), (13), and (14) defines an implicit relationship between π_s and the signal strength θ. It is easy to show that θ increases monotonically with π_s. It follows that the equilibrium π_s must rise to equilibrate the FOC. In other words, $\partial\pi_s/\partial\theta > 0$: a more positive signal is associated with a higher probability that traders will visit market *s*. This raises prices in surplus (low price) markets and lowers them in deficit (high price) markets, thereby reducing price dispersion between markets.

Theoretical Predictions

This model, albeit stylized, conveys the key intuition behind the empirical analysis. The introduction of mobile phones in Niger provided traders with access to a private signal about local supply and arguably improved the quality of such signals in terms of accuracy, detail, and timing. During our study period, the technology was primarily used by traders, with more limited access to and use by farmers. The model suggests that the introduction of mobile phone coverage should 1) lead to a shift in informed traders' attention to market *s* (i.e., the surplus market with an informative signal); 2) raise producer prices in surplus (low price) markets and lower them in deficit (high price) markets; and 3) reduce spatial price dispersion between markets with mobile phone coverage.

These effects need not be present for storable commodities because intertemporal arbitrage sets a ceiling or a floor on the price at which farmers and traders are willing to trade and can thus reduce price dispersion even in the absence of informative signals.[12] This implies that the above predictions apply primarily to perishable and semi-perishable commodities for producer prices, but not necessarily to non-perishables or for consumer prices markets, as is the case in Aker (2010). In this paper, we formally test the third hypothesis for non-perishable and semi-perishable commodities and provide suggestive evidence in support of the second hypothesis.

Data and Summary Statistics

This paper uses three primary datasets. The first is a market-level monthly panel for 37 markets over a ten-year period (1999–2008) collected by the Agricultural Market Information Service (AMIS) of Niger. This dataset includes monthly producer and consumer prices for millet, sorghum, and cowpea.[13] A producer price observation is calculated as the average monthly price that farmers received for selling a given crop in that market. Consumer prices are similarly defined. In addition, we have data on factors that may affect arbitrage, such as fuel prices, transport costs, rainfall, market latitude and longitude, and the distance and road quality between market pairs.[14] These data are combined with information on the location and date of mobile phone coverage in each market between 2001 and 2008, which was obtained from the mobile phone service providers.

The second dataset is a panel survey of traders and farmers interviewed in Niger between 2005 and 2007. The survey includes 415 traders and farmers in 35 markets and associated villages across six geographic regions of Niger. A majority of traders in Niger are male, from the Hausa ethnic group, and have never attended school. Traders search for price information in an average of 3.8 markets and buy and sell commodities in four markets. Traders have an average of 16 years' of trading experience, and only 10 percent had changed their market since they began trading (Tack and Aker 2014). Table 1A provides summary statistics for farmers. Despite their low levels of production, on average, 25 percent of farmers sold millet, and 75 percent sold cowpea. Compared to traders, farmers traded over a smaller geographic area, selling in 1.46 markets and searching for price information in 1.5 markets.

Fewer than 5 percent of the villages in the farmer survey had mobile phone coverage between 2005 and 2007, and none of the farm households in the sample owned a mobile phone. As a result, inferences drawn from this dataset have low power. To provide additional insight into the relationship between mobile phone coverage and farmers' marketing behavior, we also rely on a 2009 survey of 1,038 farm households from 100 Niger villages. The survey collected data on agricultural production and marketing behavior as well as mobile phone coverage and ownership in each village. Table 1B provides summary statistics from this survey. Overall, many of the socio-demographic indicators are similar to those of the 2005–7 survey; households have low levels of education and are primarily from the Hausa ethnic group. Millet and cowpea are the primary crops grown by farm households in our sample, followed by sorghum and peanut. More than 70 percent of households sold cowpea, compared with 36 percent of households that sold millet. Farm households purchased and sold their staple food and cash crops in 2.3 markets and primarily sold to traders located in markets. However, approximately 30 percent of households owned mobile phones by this time, a marked increase from the earlier survey.

Empirical Strategy

We first examine the impact of mobile phone coverage on producer price dispersion, comparing market pairs with and without mobile phone coverage using a difference-in-differences (DD) strategy similar to that of Aker (2010):

$$Y_{jk,t}^{i} = \beta_0 + \beta_1 mobile_{jk,t} + X_{jk,t}^{'}\gamma + \alpha_{jk} + \theta_t + \mu_{jk,t}\ , \qquad (15)$$

where $Y_{jk,t}^{i}$ is the absolute value for commodity i (millet, sorghum, and cowpea) of the difference in logged producer prices between markets j and k.[15] Furthermore, $mobile_{jk,t}$ is a binary variable equal to one in month t if both markets j and k have mobile phone coverage and 0 otherwise.[16] The α_{jk}s are market-pair fixed effects, controlling for time-invariant factors such as geographic location, urban status, and market size. The θ_ts are a vector of time fixed effects, either yearly or monthly. We also include a set of market-pair time-varying controls ($X_{jk,t}$) likely to affect spatial price dispersion, such as transport costs and the occurrence of drought.[17] The parameter of primary interest is β_1, a negative value indicates that mobile phone coverage reduces price dispersion between market pairs.

Because equation (15) is a time-series dyadic regression, standard errors must be corrected for spatial and temporal dependence. Following Aker (2010), we first cluster the standard errors at the market pair level. This allows for dependence over time within the market pair. As a robustness check, we also include market fixed effects and cluster by quarter to correct for spatial dependence across markets within a period while allowing for some dependence between months (Aker 2010, Bertrand, Duflo and Mullainathan 2004).

Equation (15) is also estimated using an alternative specification of the dependent variable, similar to Jensen (2007):

(16) $$Y_{r,t} = \beta_0 + \beta_1 mobilepercent_{r,t} + X_{r,t}^{'}\gamma + \theta_t + \alpha_r + u_{r,t} \ ,$$

where $Y_{r,t}$ is the difference in maximum and minimum producer prices across markets within a region during month t and $mobilepercent_{r,t}$ is the percentage of markets within a region that have mobile phone coverage during month t.

Identification and Assumptions

To interpret β_1 as the causal effect of mobile phone coverage on producer price dispersion, we must assume that, conditional on all covariates, $mobile_{jk,t}$ is uncorrelated with the error term. The DD specification controls for time-invariant unobservables, but we must also assume no time-varying unobservables correlated with mobile phone coverage and the outcomes of interest.

We formally test the validity of these identification assumptions in several ways. We first examine whether mobile phone coverage expanded primarily into markets where the potential for improvement in market integration was the greatest. This does not appear to be the case. Mobile phone operators cited two main determinants of tower placement: whether a location was an urban center (defined as a population of more than 35,000) and whether the location was near the southern or western borders. To verify these claims, we regress a binary variable for mobile phone coverage in location j at time t on j's urban status, latitude and longitude, elevation, slope, and road quality (Buys et al. 2009; Batzilis et al. 2010). The regression results confirm the criteria cited by mobile phone operators (Table 2): urban areas were more likely to receive mobile coverage, as were markets with paved roads, a variable that is correlated with urban status (Column 1). The eastern part of the country, with a higher density of border markets, was also more likely to receive mobile phone coverage earlier. Characteristics that are potentially correlated with high potential for market integration, such as elevation, slope, latitude, and market size, are not correlated with mobile phone expansion during our study period. These results are robust to the use of probit estimation (Column 2).

Even if agricultural market performance were not an explicit rationale behind tower placement, the possibility remains that the spatial dispersion of producer prices is correlated with pre-treatment time-invariant or time-varying characteristics that led to the placement of mobile phone towers. To determine whether this is the case, Table 3 shows the differences in means for pre-treatment (1999–2001) outcomes and covariates at the market (Panel A) and market pair level (Panel B). Overall, the results suggest that there were no statistically significant differences in pre-treatment outcomes between mobile phone and non-mobile phone markets. Most differences in pre-treatment covariates are also not statistically significant from zero, with the exception of a market's urban status, thereby confirming the earlier results. Although the pre-treatment differences in producer price levels and dispersion are not significantly different from zero for millet and sorghum, there is a statistically significant difference in the pre-treatment cowpea producer prices and dispersion. However, a statistically significant difference only exists for one of the two pre-treatment years rather than both, suggesting that this was not systematic. In addition, pre-treatment price dispersion for cowpea is lower in non-mobile phone markets. Hence, if our findings are biased because of the non-random placement of phone towers, this bias is most likely in the direction of underestimating the effect of mobile phone coverage.

The key identification assumption of equation (15) is that of parallel trends across mobile phone and non-mobile phone markets. This assumption might be violated if we do not control for time-varying characteristics, such as road quality, that are simultaneously correlated with mobile phone coverage and price dispersion. To test this possibility, we conduct a falsification test by estimating equation (15) using data from *before* the introduction of mobile phones (Table 4). The rationale behind this test is that if mobile phone and non-mobile phone markets follow different time trends, this difference should have already been apparent before mobile phone coverage was introduced. We find that the pre-intervention trends for the log of cowpea producer prices (Column 3) and cowpea and sorghum producer price dispersion (Columns 4 and 6) are not significantly different from zero for markets and market pairs that received mobile phone coverage. However, there seem to be somewhat differing trends for millet producer prices (Column 1) and producer price dispersion (Columns 1 and 2) and for sorghum producer prices. This finding raises some concerns regarding the parallel trend assumption, especially for millet price dispersion. Nevertheless, mobile phone markets had relatively higher producer price dispersion prior to treatment, suggesting that our findings may underestimate the effects on millet producer price dispersion. In addition, these differences are present during one of the pre-treatment years rather than both, suggesting that the differences are not systematic.[18]

Results

We first present the impacts of mobile phone coverage on producer price dispersion for different commodities. Because these results might differ by market characteristics, we then present heterogeneous treatment effects by distance, road quality, period of year, and market type. We end with the results on the impact of mobile phone coverage on producer-consumer margins and producer price levels.

Average Effects of Mobile Phone Coverage

Table 5 presents the regression results of equation (15) for cowpea (Columns 1-4), millet (Columns 5-8), and sorghum (Columns 9-12). According to our model, we expect mobile phone coverage to reduce price dispersion for cowpea more than for millet or sorghum because cowpea is a semi-perishable commodity. Controlling for yearly, monthly, and market pair fixed effects (Column 1), we find that mobile phone coverage reduces cowpea producer price dispersion by 6.3 percent, with a statistically significant effect at the 1 percent level. This result is robust to the introduction of additional covariates that also affect producer price dispersion across markets (Column 2), such as drought and transport costs. The result is also similar when including market fixed effects with the standard errors clustered by quarter (Column 3). Similar to Aker (2010), we also include a binary variable equal to one when only one market in a pair has mobile phone coverage (Column 4). The effect of mobile phones is still negative and statistically significant when both markets are treated. Using the most conservative estimate of all of the specifications, the introduction of mobile phones is associated with a 6 percent reduction in cowpea producer price dispersion compared to market pairs without mobile phones in the pre-treatment period.[19]

Columns 5 to 12 contain similar regressions for millet and sorghum, two less perishable commodities. Mobile phone coverage reduces millet producer price dispersion across markets by as little as 0.1 percent without a statistically significant effect. The magnitude and statistical significance of this effect is similar across all specifications (Columns 5-8) and is similar for sorghum. Taken together, these results are consistent with the idea that for non-perishable commodities such as millet and sorghum, even limited intertemporal storage may act as a buffer on local market price fluctuations, keeping prices aligned across producer markets even in the absence of market information.

A concern with the price data is the presence of missing observations. Because the demand for staple grains is relatively constant throughout the year, consumer price data are readily available for each market and each month (Aker 2010). In contrast, farmers in Niger do not have sufficient stocks to sell throughout the year. As a result, producer price data are not available for some markets during certain periods of the year, especially during the season immediately prior to the annual harvest.

To check the robustness of our results to potential selection bias generated by missing data, we re-estimate equation (15) in two different ways. We first use a two-stage Heckman procedure, estimating a selection equation on market-pair data and adding the resulting inverse Mills' ratio as a separate regressor to equation (15) (Heckman 1979). These results are shown in the supplemental appendix (Tables S1 and S2, available at http://wber.oxfordjournals.org/). The results for cowpea are similar in magnitude and statistical significance to those reported in Table 5. We also re-estimate equation (15) using a balanced panel of market pairs that have a full set of price data for all time periods in the sample (Table S2, columns 5-8). The point estimates are slightly smaller (a 4 percent reduction in price dispersion), but the coefficient estimates remain significant at the 1 percent level.

The results for millet *producer* prices presented here differ from the results of Aker (2010), who found that mobile phone coverage reduces *consumer* price dispersion for millet by 10 percent (Aker 2010). Both findings are consistent if millet is stored primarily in production areas. When there are insufficient stocks in consumer markets, unanticipated demand shocks are a source of price fluctuation. The effect of shocks on consumer prices can only be smoothed if traders can quickly determine where to send more supplies. Using the Section 3 model in reverse, we see that by facilitating the efficient allocation of millet from producer to consumer markets, mobile phones can explain the reduction in price dispersion across consumer markets.

Table 6 presents results based on equation (16) using the max-min producer price spread (in CFA/kg) of markets across a region as the dependent variable (Jensen 2007). The key independent variable of interest is the intensity of mobile phone coverage within a region ($mobilepercent_{r,t}$) rather than the coverage status of a particular market or market pair. Controlling for year and region fixed effects, we find that an increase in the density of mobile phone within a region leads to a reduction of 36 CFA/kg in the max-min price spread of cowpea producer prices (Column 1), with a statistically significant effect at the 5 percent level. There is no statistically significant impact on the max-min producer price spread for millet (Column 2) or sorghum (Column 3). Although the interpretation of equation (16) is not directly comparable to (15), the results in Table 6 demonstrate that our findings are not an artifact of the dyadic specification.

Heterogeneous Effects of Mobile Phone Coverage

From our theoretical model, the effect of mobile phone coverage on producer price dispersion is predicted to be larger for markets and time periods in which access to information reduces the spatial misallocation of traders across markets. We expect coordination failures among traders to be strongest when search costs are high, i.e., when markets are distant and transport costs are large because of poor quality roads. In addition, we expect trader miscoordination to be highest and the benefits from mobile phones to be largest at times of the year when markets are thin (i.e., outside of the harvest period). Heterogeneous effects by market type, whether surplus or deficit, depend on the commodity. For semi-perishable crops, both deficit and surplus markets experience shocks that cannot be smoothed by storage and thus benefit from better spatial arbitrage. For less perishable crops such as millet and sorghum, inter-temporal arbitrage reduces the potential benefits from spatial arbitrage. Because grain storage in Niger is undertaken predominantly by market agents near surplus markets, we would therefore expect mobile phone coverage to reduce millet and sorghum price dispersion primarily in deficit markets, with ambiguous predictions for cowpea.

Table 7 estimates the heterogeneous effects of mobile phone coverage on producer price dispersion.[20] The regression specifications are similar to those in Table 5, except for the inclusion of the interaction term and the heterogeneous effect. Column 1 looks at the heterogeneous effect by distance, a binary variable that is equal to one if markets are more than 350 km apart. Consistent with the theoretical predictions, the interaction term is negative and statistically significant at the 1 percent level, implying that mobile phone coverage reduces price dispersion by 7 percent for markets located more than 350 km apart, compared to a 5 percent reduction for markets in closer proximity. Column 2 includes an interaction term between mobile phone coverage and a binary variable for paved roads. Although the coefficient is positive and consistent with the theoretical predictions, this effect is not statistically significant at conventional levels. Looking at the impact by period of year (Column 3), the coefficient on the interaction term is positive and statistically significant, suggesting that mobile phone coverage reduces producer price dispersion *less* during the harvest period compared with other seasons, again in agreement with theoretical predictions. Finally, Columns 4 and 5 introduce an interaction term between mobile phone coverage and market type ("surplus" market), which is defined as a market with surplus production.[21] In Column 4, the surplus variable is equal to one if both markets in a pair are surplus markets and 0 otherwise. In Column 5, the variable is equal to one if one market is a surplus market and the other is a deficit market. The coefficient estimates are negative, suggesting that the reduction in price dispersion is stronger in surplus markets compared with deficit markets. The magnitude of the effect is small, however, and is not statistically significant in Column 5.

We find similar results for millet (columns 6-10) and sorghum (Table S3). The interaction term between mobile phone coverage and the distance is negative and statistically significant at the 1 percent level, suggesting that mobile phone coverage reduces millet producer price dispersion by 2 percent for markets located more than 350 km apart, though it has no significant impact for nearby markets. Column 2 presents the results for road quality. The coefficient on the interaction term is again positive and statistically significant, indicating that, as predicted, mobile phone coverage is less useful in reducing price dispersion for markets connected by paved roads. Column 3 presents the results by season. The interaction between mobile coverage and harvest season is, as before, positive and statistically significant, suggesting that mobile phone coverage has a stronger impact on producer price dispersion during the non-harvest period. In the last two columns, we interact mobile phone coverage with market type. The results are inconclusive; the coefficient estimates are negative in column 9 but positive in column 10.

Effects on Gross Trade Margins and Producer Prices

The previous results show that the introduction of mobile phone coverage reduced cowpea producer price dispersion, with stronger effects for markets where there was potential miscoordination among traders. With the introduction of mobile phone coverage, improved information flows are expected to reduce traders' costs. With sufficient competition among traders, reduced trade costs should reduce the average gross trade margin, that is, the difference between average consumer and producer prices in a market.[22] As a result, consumer prices should fall on average, and/or producer price levels should rise. This effect only operates through gross trade margins reduced by improved spatial arbitrage and should thus only affect price differences between geographically distinct surplus and deficit markets, especially if inter-temporal arbitrage is not feasible.[23]

To investigate whether mobile phone coverage affected gross trade margins, we estimate equation (15) using the absolute value of the difference in logged consumer prices in market *j* (a deficit market) and logged producer prices in market *k* (a surplus market). The sample only includes market pairs with a deficit and surplus market. In this specification, β_1 measures the percentage reduction in the gross trade margins associated with the introduction of mobile phone coverage.[24]

In an effort to understand how and whether mobile phone coverage affected the components of the gross margin, we also estimate the following equation,

$$Y^{i}_{j,t} = \beta_0 + \beta_1 mobile_{j,t} + X^{'}_{j,t}\gamma + \alpha_j + \theta_t + \mu_{j,t} \,, \tag{17}$$

with two dependent variables: (1) the log of producer prices in surplus market j in month t and (2) the log of consumer prices in deficit market j in month t. In this specification, $mobile_{j,t}$ is a binary variable equal to one at month t if market j has mobile phone coverage and 0 otherwise. $X_{j,t}$ is a vector of control variables thought to affect producer price levels on market j, such as the occurrence of drought. The θ_j's are market fixed effects, controlling for geographic location, urban status, and market size, and θ_t are time fixed effects (either monthly or yearly) that control for time-varying aggregate factors. Standard errors are clustered at the market level. We also use the intra-annual price coefficient of variation of commodity i on market j at year t as an alternative measure of producer welfare to producer prices.

Table 8 presents the regression results for gross trade margins and equation (17) for cowpea (Columns 1-4) and millet (Columns 5-8). We find no statistically significant effects of mobile phone coverage across markets on gross trade margins for cowpea (Column 1), millet (Column 5), or sorghum (not shown). One possibility is that the efficiency gains (i.e., economizing on search costs) were not large enough to yield a statistically significant reduction in gross margins. It is also conceivable that the net margins improved for traders but that this improvement did not occur during the study period.

Turning to the regression results for equation (17), we find no effect of mobile phone coverage on producer price levels in surplus markets for cowpea (Column 2), millet (Column 6), or sorghum (not shown). For deficit markets, we also do not find any statistically significant effects of mobile phone coverage on consumer prices for any of the commodities.[25] These findings are in line with our earlier findings that gross margins did not fall, even for cowpeas. They are also consistent with our model, which predicts a reduction in the spatial variance of prices but not necessarily an effect on average prices across surplus or deficit areas. It is also conceivable that our categorization of surplus and deficit markets is too imprecise. A market's "surplus" or "deficit" status may vary across seasons and years. In the absence of time-varying data on trade flows, we can only categorize markets based on the average trading patterns, which might be an oversimplification.[26]

Using the intra-annual coefficient of producer price variation as the dependent variable, we find that mobile phone coverage reduces the average intra-annual coefficient of variation by 6 percentage points for cowpea, with a statistically significant effect at the 1 percent level (Column 4). Given that the pre-treatment intra-annual coefficient of variation of cowpea price is 26 percent, this represents a 23 percent reduction in the intra-annual price risk for cowpea farmers in Niger. We find negative but not statistically significant effects for millet (Column 8) and sorghum (not shown). These findings are also in line with the model predictions in that better spatial arbitrage reduces week-to-week price variation, but only when this role cannot be assumed by inter-temporal arbitrage.

A limitation of the market-level data is that mobile phone coverage at the village level was still relatively limited by 2008 and expanded considerably into villages after that period. Thus, we might be underpowered to estimate effects on producer prices. To gain more insight into this issue, we use a farm household survey collected by one of the authors in 2009, by which time mobile phone coverage had begun to reach more rural areas. Across the 100 villages in our sample, all had mobile phone coverage by 2009, and 30 percent of the farmers in these villages owned mobile phones. Although there are obvious limitations to using this cross-sectional survey, the data provide a useful comparison to the market-level data.

Our dependent variable of interest is the log of producer prices received for a variety of perishable and semi-perishable commodities, namely millet, sorghum, cowpea, peanut, sesame, onion, calabash, and okra. The estimating equation is

$$Y_j^i = \beta_0 + \beta_1 mobileown_j + X_j^{'}\gamma + \alpha_k + \mu_{jk} , \tag{18}$$

where Y_j is the log price of commodity *i* received by farmer *j*, *mobileown* is a binary variable for whether the household owns a mobile phone, X_j is a vector of farmer-specific covariates to control for factors that potentially affect mobile phone ownership and prices received (such as land ownership, asset ownership, gender, and ethnicity), and α is a set of village fixed effects. Farmers with a phone may access price information more easily, but this will not be reflected in a higher producer price unless farmers can use this information for arbitrage. β_1 may be biased upward if mobile phone ownership is correlated with time-varying unobserved factors, such as motivation or intrinsic marketing ability.

Table 9 shows the results for equation (18). For all commodities except peanuts, mobile phone ownership is not associated with a significantly higher price received (Panel A).[27] These findings are similar to Fafchamps and Minten (2012), who show that a mobile phone-based price information intervention in India is not associated with a higher producer price levels. However, these findings stand in contrast to Jensen (2007), who finds that mobile phone coverage increases producer prices. Jensen (2007) examines the impact of mobile phone coverage on producer prices in a context with a highly perishable commodity (fish) in which producers (fishermen) have a strong comparative advantage in spatial arbitrage.[28]

Mechanisms

To understand the mechanisms behind our market-level results, we look for direct evidence of information acquisition and arbitraging behavior among different market agents (farmers and traders). Our model suggests that mobile phone coverage improved *traders'* access to information on producer prices in different markets, thereby facilitating spatial arbitrage. At the same time, mobile phone coverage may improve *farmers*' access to information, thereby allowing them to engage in spatial arbitrage.

Tack and Aker (2014) measure the impact of mobile phone coverage on traders' behavior, primarily focusing on their search behavior. Using the trader-level dataset, they find that mobile phone coverage is associated with an increase in traders' numbers of search markets and the number of market contacts, with statistically significant effects. Although they do not provide direct evidence of a change in traders' arbitrage behavior, the results do not appear to be driven by traders' selection into mobile phone markets, changes in the composition of traders, or increased collusion among traders.

Table 9 (Panel B) provides some suggestive evidence of the impact of mobile phone coverage on farmers' behavior using a specification similar to equation (18). Although the coefficient estimates are biased, we find that mobile phone ownership is associated with an increase in farmers' probability of searching for price information and that mobile phones became a more useful source of such information. Unlike the trader results, farmers with mobile phones do not increase the number of search markets or the number of sales and purchase markets.[29] This finding suggests that despite increased access to information, farmers in Niger did not change their marketing behavior.

Conclusion

This paper provides some estimates of the nature, magnitude, and distribution of the effects of mobile phones on market performance in Niger. Although mobile phone coverage did not reach remote rural areas during the period of our sample, it reduced the spatial dispersion of producer prices for cowpea, a semi-perishable commodity. It did not affect spatial price dispersion for millet or sorghum, two storable grains. We also find a stronger reduction in producer price dispersion in remote markets and during periods when markets were thin. The reduction in price dispersion did not increase the average producer prices, but it did reduce the intra-annual price variation for cowpea.

This paper provides additional empirical evidence of the importance of informative signals for market efficiency and the differential impacts by crop. Combined with the results in Aker (2010) and Tack and Aker (2014), our results indicate that the introduction of mobile phones generated net efficiency gains in agricultural markets in Niger. However, we find no evidence suggesting that these gains translate into higher average prices for the primary suppliers of these commodities.

These findings are central to the current debate on the role of information technology in promoting economic development. Information technology is often considered a low development priority. However, some believe that by reducing communication costs over long distances, mobile phones can reduce poverty among rural households. The results presented here indicate that the impact of technology can differ substantially by the type of crop, the type of market, and the time of year, even within the same country. Differences in impact can be linked to differences in arbitrage opportunities and market behavior for these crops and between agents.

Notes

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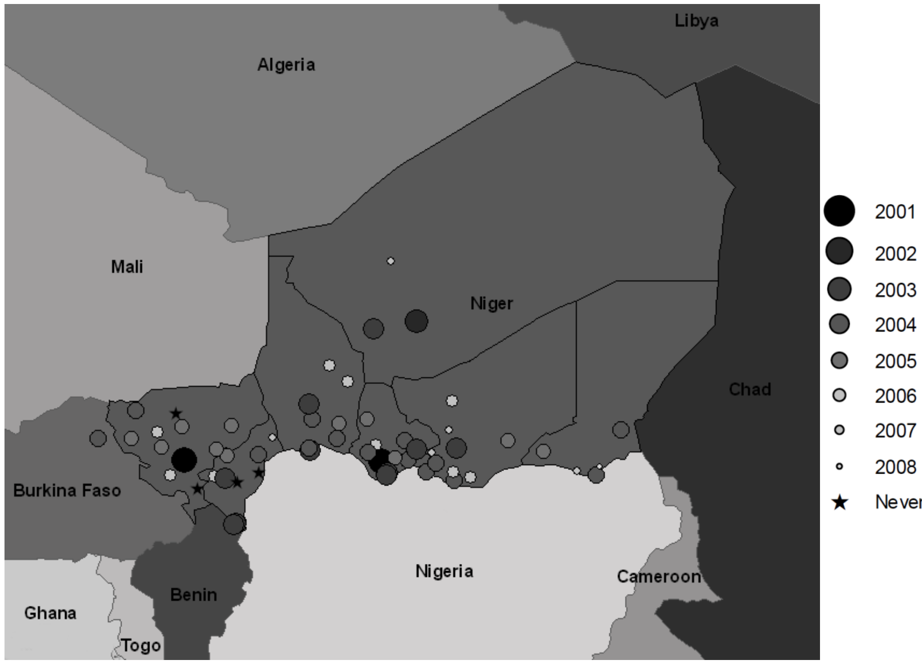
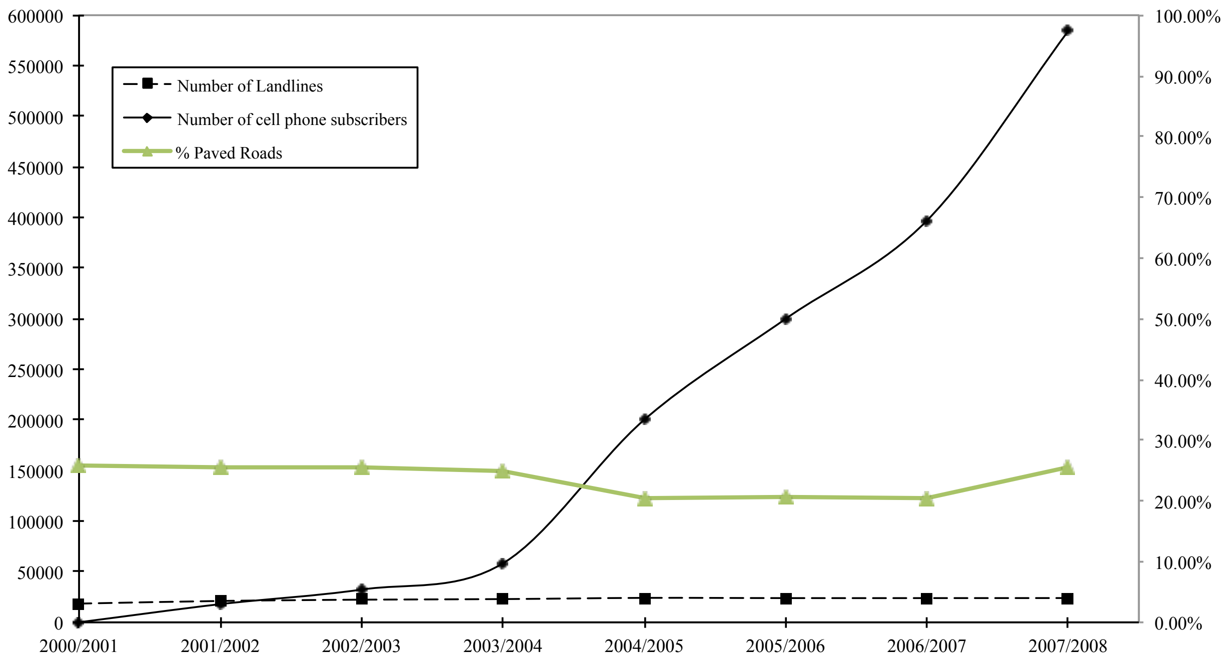
Figure 1. Mobile Phone Coverage by Market and Year, 2001–8



Notes: Data collected from mobile phone companies in Niger (Zain/Airtel, Moov, and Sahelcom). The map shows mobile phone coverage for grain markets between 2001 and 2008.

Figure 2. Mobile Phone Subscribers, Landlines, and Road Quality, 2001–8



Notes: Raw data obtained from Sonatel/Niger (number of landlines), Wireless Intelligence (number of mobile phone subscribers), and the World Bank (http://data.worldbank.org/country/niger).

Table 1A. Summary Statistics Farmer Survey 2005–7

Panel A: Farmer-Level Characteristics	Sample Mean (s.d.)
Socio-Demographic Characteristics	
Age of respondent	49(16)
Gender of respondent (male=0, female=1)	.01(.09)
Education of respondent (0=elementary or above, 1=no education)	.85(.35)
Member of Hausa ethnic group	.675(.469)
Panel B. Agricultural Marketing Activities	
Sold millet in the past year	0.25
Sold cowpea in the past year	0.56
Purchased millet since the previous harvest	0.91
Number of hours walking to principal market	1.53
Access to a paved road	.269(.444)
Number of purchase and sales markets	1.46(.670)
Member of a producers' association	0.22
Sold to intermediary since the last harvest	0.45
Bought agricultural products on credit in the past year	0.41
Received payment in advance for harvest	0.16
Responsible for transport if selling product	0.64
Household follows market price information	
Personal conversations with traders and farmers	0.75
Radio (MIS)	0.09
Other	0.14

Source: Authors’ own survey work in Niger based upon a Niger farmer survey conducted between 2005 and 2007.
Notes: Total sample size is 200 farmers across 37 villages across five regions of Niger. Respondents are primarily the household head.

Table 1B. Summary Statistics Farmer Survey 2008

Panel A: Farmer-Level Characteristics	**Sample Mean (s.d.)**
Socio-Demographic Characteristics	
Age of respondent	37.5 (12.44)
Gender of respondent (male=0, female=1)	.5 (.5)
Education (0=No education, 1=Some education (including Coranic)	.08 (.264)
Member of Hausa ethnic group (1=Hausa, 0 otherwise)	.72 (.45)
Household size	8.37 (4.06)
Household owned mobile phone in 2008	.29 (.46)
Number of mobile phones owned	.37 (.65)
Panel B. Agricultural Marketing Activities	
Cultivated millet during previous harvest	.99 (.06)
Cultivated sorghum during previous harvest	.79 (.41)
Cultivated cowpea during previous harvest	.95 (.23)
Cultivated peanut during previous harvest	.56 (.50)
Sold millet since previous harvest	.36 (.48)
Sold sorghum since previous harvest	.09 (.29)
Sold cowpea since previous harvest	.70 (.46)
Sold peanut since previous harvest	.49 (.50)
Purchased millet since previous harvest	.35 (.48)
Purchased sorghum since previous harvest	.12 (.32)
Purchased cowpea since previous harvest	.11 (.32)
Purchased peanut since previous harvest	.05 (.23)
Number of purchase and sales markets for grains and cash crops	2.35 (1.26)
Member of a producers' association	.38 (.49)
Sold to trader in village since previous harvest	.17 (.38)
Sold to trader in market since previous harvest	.65 (.48)
Household follows market price information	.75 (.43)

Source: Data from a baseline survey collected for Project ABC in 2009 (Aker, Ksoll and Lybbert 2012).
Notes: The total sample size is 1,038 farm households across 100 villages in two regions of Niger. Respondents are either men or women within the household who are eligible for an adult education program.

Table 2. Determinants of Mobile Phone Coverage in Niger

Dependent variable: Mobile phone coverage (=1) in market *j* at time *t*

	(1)	(2)
Log(elevation)	0.00	0.01
	(0.15)	(0.43)
Dummy slope	0.02	0.06
	(0.06)	(0.17)
Urban center	0.28***	0.77***
	(0.05)	(0.14)
Road quality	0.04	0.13
	(0.05)	(0.16)
Latitude	-0.01	-0.04
	(0.03)	(0.09)
Longitude	0.01	0.03
	(0.01)	(0.03)
Market size	-0.00	-0.00
	(0.00)	(0.00)
Constant	0.34	-0.45
R^2	0.09	0.066
Number of observations	4032	4032

Source: Data collected from the mobile phone operators in Niger between 2001 and 2008, as well as the authors' own market survey.
Notes: Mobile phone coverage is equal to 1 in market *j* at time *t* if the market received mobile phone coverage and 0 otherwise. The slope variable is equal to 1 if the market is steeply sloped and 0 otherwise. Urban center is equal to 1 if the market has a population greater than 35,000 and 0 otherwise. Road quality is equal to 1 if the market has access to a paved road and 0 otherwise. Column 1 is OLS estimation, and Column 2 is probit estimation. *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 3. Pre-Treatment Comparison of Means by Mobile Phone Coverage (1999–2001)			
	Unconditional Mean		**Difference in Means**
	(1)	(2)	(3)
	Mobile Phone Coverage Mean (s.d.)	**No Mobile Phone Coverage Mean (s.d.)**	**Difference in Means s.e.**
Panel A. Market Level Data			
Millet Producer Price level (CFA/kg)	100.16	93.13	6.16
	(28.28)	(30.93)	(4.09)
Cowpea Producer Price level (CFA/kg)	151.75	135.2	16.56***
	(44.39)	(36.05)	(5.05)
Sorghum Producer Price level (CFA/kg)	84.24	90.62	6.39
	(33.27)	(29.99)	(4.99)
Drought in 1999 or 2000	0.058	0.063	-0.00
	(0.23)	(0.24)	(0.03)
Hausa Ethnic Group (Hausa=1)	0.62	0.75	-0.13
	(0.49)	(0.44)	(0.24)
Road Quality to Market (1=paved)	0.66	0.5	0.16
	(0.47)	(0.50)	(0.27)
Market Size (More than 100 traders=1)	0.34	0.5	-0.16
	(0.47)	(0.50)	(0.27)
Distance (km) to International Border	91.32	92.39	-1.08
	(64.96)	(54.06)	(29.92)
Urban center(>=35,000)	0.35	0	0.35***
	(0.48)	(0.00)	(0.09)
Panel B. Market Pair Level Data			
|Ln (Millet Producer Price Dispersion)|	0.13	0.13	0.00
	(0.15)	(0.13)	(0.01)
|Ln (Cowpea Producer Price Dispersion)|	0.2	0.17	0.03***
	(0.18)	(0.14)	(0.01)
|Ln (Sorghum Producer Price Dispersion)|	0.20	0.21	0.01
	(0.05)	(0.16)	(0.01)
Distance between Markets (km)	371.57	379	-7.93
	(225.36)	(245.44)	(71.11)
Road Quality between Markets (both paved=1)	0.397	0.5	-0.10

	(0.49)	(0.50)	(0.15)
Transport Costs between Markets (CFA/kg)	10.8	11	-0.21
	(6.00)	(6.53)	(1.88)

Sources: Agricultural Market Information System (AMIS) (market prices), SONIDEP (fuel prices), Direction de la Meteo (drought), mobile phone operators (mobile phone coverage) and authors' own work (market size, road quality, transport costs).

Notes: In Panel A, "mobile phone" markets are those that received coverage at some point between 2001 and 2008; "no mobile phone" markets are those markets that never received coverage during this period. In Panel B, "mobile phone" market pairs are pairs in which both markets received mobile phone coverage at some point between 2001 and 2008; "no mobile phone" market pairs are those pairs in which either one or both markets never received mobile phone coverage during this period. Huber-White robust standard errors clustered by market (Panel A) and by market pair (Panel B) are in parentheses. * significant at the 10 percent level, ** significant at the 5 percent level, *** significant at the 1 percent level. Prices are deflated by the Nigerien Consumer Price Index.

Table 4. Pre-Treatment Producer Price Trends by Mobile Phone Coverage

Commodity	**Millet**		**Cowpea**		**Sorghum**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	$\ln(P_{it})$	$\lvert\ln(P_{it})-\ln(P_{jt})\rvert$	$\ln(P_{it})$	$\lvert\ln(P_{it})-\ln(P_{jt})\rvert$	$\ln(P_{it})$	$\lvert\ln(P_{it})-\ln(P_{jt})\rvert$
	Coef. (s.e.).	Coef. (s.e.).	Coef. (s.e.).	Coef. (s.e.).	Coef. (s.e.).	Coef. (s.e.).
Mobile phone market*time	-0.08**	0.02*	-0.01	-0.02	-0.10**	0.02
	(0.03)	(0.01)	(0.04)	(0.02)	(0.04)	(0.02)
Time (=1 if 2000/2001, 0 if 1999/2000)	0.56***	-0.04***	0.09*	-0.09***	0.20***	-0.07***
	(0.04)	(0.00)	(0.04)	(0.02)	(0.05)	(0.02)
Market fixed effects	Yes	No	Yes	No	Yes	No
Market pair fixed effects	No	Yes	No	Yes	No	Yes
Additional covariates	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.08	0.73	0.12	0.88	0.1
Number of observations	423	7,190	408	6,696	302	3,718

Source: Agricultural Market Information System (AMIS) (market prices), SONIDEP (fuel prices), Direction de la Meteo (drought), mobile phone operators (mobile phone coverage) and authors' own work (market size, road quality, transport costs).
Notes: Huber-White robust standard errors clustered by market (Columns 1 and 3) or market pair (Columns 2 and 4) are in parentheses. * significant at the 10 percent level, ** significant at the 5 percent level, *** significant at the 1 percent level. All prices are in 2001 CFA.

Table 5. Impact of Mobile Phone Coverage on Producer Price Dispersion

	Cowpea				Millet				Sorghum			
Dependent variable: $\lvert \ln(P_{it})-\ln(P_{jt}) \rvert$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Mobile coverage both markets	-0.06***	-0.06***	-0.06***	-0.08***	0.00	0.00	0.00	0.00	0.00	-0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
Mobile coverage one market				-0.01***				-0.00				-0.00
				(0.00)				(0.00)				(0.01)
Other covariates	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Market pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Market pair-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	39,120	39,120	39,120	39,120	39,002	39,002	39,002	39,002	13,280	13,280	13,280	13,280
R-squared	0.154	0.165	0.37	0.38	0.09	0.09	0.32	0.32	0.10	0.10	0.20	0.20

Sources: Agricultural Market Information System (AMIS) (market prices), SONIDEP (fuel prices), Direction de la Meteo (drought), mobile phone operators (mobile phone coverage) and authors' own work (market size, road quality, transport costs).

Notes: For market pairs, mobile phone coverage = 1 in period t when both markets have mobile phone coverage and 0 otherwise. Additional covariates include CFA/kg inter-market transport costs at time t and the presence of drought in both markets at time t. Huber-White robust standard errors clustered by market pair are in parentheses in Columns 1, 2, 4 and 5, 6, and 8. Huber-White robust standard errors clustered at the quarterly level are also provided in Columns 3 and 7. All prices are deflated by the Nigerien Consumer Price Index (CPI). *** significant at the 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 6. Impact of Mobile Phone Coverage on Alternative Measures of Producer Price Dispersion

	Cowpea	Millet	Sorghum
Dependent variable: Max-Min Price Spread (CFA) within a Region	**(1)**	**(2)**	**(3)**
Percentage of markets with mobile phone coverage in region *j* at time *t*	-36.90**	2.06	20.72
	(9.40)	(3.08)	(11.11)
Additional covariates	No	No	No
Year fixed effects	Yes	Yes	Yes
Monthly fixed effects	Yes	Yes	Yes
Number of observations	3,107	3,029	2,094
R-squared	0.42	0.36	0.460

Source: Agricultural Market Information System (AMIS) (market prices), SONIDEP (fuel prices), Direction de la Meteo (drought), mobile phone operators (mobile phone coverage) and authors' own work (market size, road quality, transport costs).
Notes: The max-min price spread is the difference between the maximum and minimum producer price for cowpea among markets in a given region at time t. The coefficient of variation is the standard deviation of producer prices among markets in a region a time t divided by the mean of producer prices for markets in a region at time t. Huber-White robust standard errors clustered at the regional level are in parentheses. *** significant at the 1 percent level, ** significant at the .05 percent level, and * significant at the .10 percent level.

Table 7. Heterogeneous Impact of Mobile Phones on Producer Price Dispersion

	Cowpea					Millet				
Dependent variable: $\|\ln(P_{it})-ln(P_{jt})\|$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Mobile coverage both markets	-0.05***	-0.07***	-0.07***	-0.06***	-0.06***	0.01	-0.00	-0.01	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mobile coverage*distance (distance=1 if >350 km)	-0.02***					-0.02***				
	(0.01)					(0.01)				
Mobile coverage*road quality (Paved=1)		0.01					0.01**			
		(0.01)					(0.00)			
Mobile coverage*harvest (Harvest=1)			0.02**					0.02***		
			(0.01)					(0.00)		
Mobile coverage*surplus market (Both markets are surplus=1)				-0.01**					-0.01*	
				(0.00)					(0.00)	
Mobile coverage*surplus market (One market is surplus=1)					-0.01					0.01**
					(0.00)					(0.00)
Joint effect significant	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	38,820	38,820	38,820	38,820	38,820	38,714	38,714	38,714	38,714	38,714
R-squared	0.38	0.37	0.37	0.37	0.37	0.0938	0.32	0.32	0.32	0.32

Sources: Agricultural Market Information System (AMIS) (market prices), SONIDEP (fuel prices), Direction de la Meteo (drought), mobile phone operators (mobile phone coverage) and authors' own work (market size, road quality, transport costs).

Notes: Each column is a separate regression. For market pairs, mobile phone coverage = 1 in period t when both markets have mobile phone coverage and 0 otherwise. Additional covariates include CFA/kg inter-market transport costs at time t and the presence of drought in one market. Huber-White robust standard errors clustered by market pair are in

Table 8. Impact of Mobile Phone Coverage on Gross Margins and Prices

	Cowpea				Millet		
Dependent variable:	***ln*(*PC*$_{it}$)-*ln*(*PP*$_{it}$)**	***ln*(*P*$_{it}$)**	***ln*(*C*$_{it}$)**	**Intra-annual CV**	***ln*(*PC*$_{it}$)-*ln*(*PP*$_{it}$)**	***ln*(*P*$_{it}$)**	***ln*(**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7**
Mobile phone coverage	0.01	0.00	0.018	-0.06***	-0.00	-0.00	-0.0
	(0.01)	(0.02)	(0.013)	(0.02)	(0.01)	(0.01)	(0.0
Other covariates	Yes	Yes	Yes	No	Yes	Yes	Ye
Market pair fixed effects	Yes	No	No	Yes	Yes	No	N
Market fixed effects	No	Yes	Yes	Yes	No	Yes	Ye
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Ye
Monthly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Ye
Market-specific time trends	No	Yes	Yes	Yes	No	Yes	Ye
Cross-border markets	No	No	No	No	Yes	No	N
Number of observations	28,035	1,193	1,861	3,033	27,958	1,153	1,8
R-squared	0.52	0.84	0.74	0.44	0.60	0.89	0.8

Source: Agricultural Market Information System (AMIS) (market prices), SONIDEP (fuel prices), Direction de la Mete mobile phone operators (mobile phone coverage) and authors' own work (market size, road quality, transport costs).
Notes: For market pairs, mobile phone coverage = 1 in period t when both markets have mobile phone coverage and 0 o Columns 1, 5, and 9 are the difference in log consumer prices in deficit markets and producer prices in surplus markets. and 10 are the log of producer prices in surplus markets, whereas Columns 3, 7, and 11 are the log of consumer prices ir Additional covariates include the presence of drought in both markets at time t. Huber-White robust standard errors clus pair are in parentheses. All prices are deflated by the Nigerien Consumer Price Index (CPI). *** significant at the 1 perc significant at the 5 percent level, * significant at the 10 percent level.

Table 9. Correlation between Mobile Phone Ownership, Producer Prices, and Farmers' Marketing Behavior

	(1)	(2)
	Mean of Non-Mobile Phone Households	**Coeff (s.e.)**
Panel A: Producer Prices		
ln(Producer Price Millet)	158	-0.09
	(51)	(0.12)
ln(Producer Price Sorghum)	139	-0.17
	(55)	(0.16)
ln(Producer Price Cowpea)	207	0.01
	(139)	(0.04)
ln(Producer Price Peanut)	117	0.07
	(53)	(0.05)
ln(Producer Price Millet-Market Price Millet)	-0.12	-0.11
	(0.46)	(0.13)
ln(Producer Price Millet-Market Price Cowpea)	-0.23	0.06
	(0.52)	(0.09)
ln(Producer Price Millet-Market Price Peanut)	-166	-114.09
	(414)	(213.81)
Number of observations	411	
Panel B: Farmer Marketing Behavior		
Household follows price information	0.73	0.07*
	(0.44)	(0.03)
Price information from traders market useful	0.66	-0.10***
	(0.47)	(0.04)
Price information from mobile phones useful	0.12	0.12***
	(0.32)	(0.03)
Price information from friends useful	0.71	-0.08*
	(0.45)	(0.05)
Number of purchase and sales markets	2.3	0.14
	(1.17)	(0.12)
Number of observations	811	

Source: Data from a baseline survey collected for Project ABC in 2009 (Aker, Ksoll and Lybbert 2012).
Notes: The total sample size is 1,038 farm households across 100 villages in two regions of Niger. Respondents are either men or women within the household who are eligible for an adult education program. Each row represents a separate regression, controlling for household mobile phone ownership, ethnicity, gender, and village-level fixed effects. Huber-White robust standard errors clustered at the village level are in parentheses. * significant at the 10 percent level, ** significant at the 5 percent level, *** significant at the 1 percent level.

[1] Aker (2008) shows that grain traders store an average of one week, with larger traders (wholesalers) storing for an average of one month. Storage duration data were not available by commodity. Farmer-level data collected by one of the authors suggests that farmers primarily produce cowpea as a cash crop and sell soon after the harvest, thus implying limited storage, and they store millet and sorghum for longer periods.

[2] In surveys with agricultural traders and producers between 2005 and 2007, an overwhelming majority (87 percent) stated that they did not access or use price information provided Agricultural Market Information System (AMIS), primarily because of the type of data (only consumer prices are provided) and the timing of the data diffusion (the data are provided weekly, in some cases six days after a market).

[3] Based on one of the author's interviews with mobile phone service providers in Niger. The primary priority borders were those in the southern areas of the country (Nigeria, Burkina Faso, and Mali) rather than the north (Libya, Algeria).

[4] Figure 2 is similar to that presented in Aker (2010), but it extends the data until 2008 and adds data on road quality.

[5] Since 2008, mobile phone coverage and adoption have expanded considerably in rural areas. The 2009 survey conducted by one of the authors revealed that mobile phone ownership had reached 29 percent in rural areas.

[6] Jensen (2007, 2010) develops a model outlining the welfare implications of costly search under exogenous supply, focusing primarily on the farmers' perspective.

[7] Agricultural traders in Niger also typically relied upon personal travel to obtain price information prior to the introduction of mobile phones.

[8] In 2008, a two-minute call to a market located 10 km away cost US$.50, compared to US$1 for round-trip travel using a market truck or cart.

[9] This scenario encompasses two possibilities. The first is that traders and markets are placed at regular intervals on a lattice or Taurus, and traders cover partially overlapping geographical areas. The second is that n traders cover the same n producer markets and sell in the same consumer market.

[10] Systematic differences in $F(q)$ across markets would generate systematic differences in average price. However, in the first approximation, this should not affect the spatial integration of prices.

[11] We only consider symmetric equilibria (thus ruling out a situation whereby traders coordinate on a public randomization device), which implies that the only Nash equilibria is for each trader to randomize among each market with equal probability.

[12] To illustrate our model, assume that traders receive no information about market prices, and imagine that the agricultural commodity can be stored by farmers. Consider farmers in market m who are offered a low price because few traders happen to visit market m on that day. Rather than selling at a low price, they can store and sell later, when more traders visit the market. In this case, intertemporal arbitrage will smooth prices in market m across time (Williams and Wright 1991). As a result, prices in different markets cannot diverge simply because the number of traders who visit each market varies in a stochastic manner.

[13] Because sorghum requires more rainfall than millet, it is grown in fewer geographic locations in Niger, primarily in the southern areas of the country. As a result, sorghum price data are available for fewer markets and during fewer periods and hence are subject to more missing observations than the cowpea or millet producer price data.

[14] These data were obtained from the *Syndicat des Transporteurs Routiers*, the *Direction de la Météo* in Niger, and the trader survey.

[15] Various dependent variables have been used in the literature to measure price dispersion. The consumer search literature has used the sample variance of prices across markets over time (Pratt, Wise, and Zeckhauser 1979), the coefficient of variation (CV) across markets (Eckard 2004; Jensen 2007), or the maximum and minimum prices across markets (Pratt, Wise, and Zeckhauser 1979; Jensen 2007). The international trade literature has used the log of the price ratio between two markets or the standard deviation of price differences across markets (Engel and Rogers 1996; Parsley and Wei 2001; Ceglowski 2003; Aker 2010). We adopt the latter approach for our core specification, but we also use the CV and the max-min as alternative specifications.

[16] In all specifications, "treatment" is defined as the presence of a mobile phone tower rather than mobile phone adoption.

[17] A market's urban status did not change between 1999 and 2008, so this is controlled for by including market pair and market fixed effects. Road quality in Niger was fairly stagnant during the time period under consideration. In 1995, Niger had 3,526 km of paved roads, increasing to 3,761 km in 2008, with the primary improvement occurring in 1997 (prior to mobile phone coverage) (Figure 2). Among the markets in our sample, only 16 percent of markets received some type of road improvement between 1999 and 2008, with the majority of this improvement occurring in 2007/2008, toward the end of our sample period and well after mobile phone coverage was introduced into these markets.

[18] These tests do not control for other time-varying unobserved factors that might be simultaneously correlated with mobile phone coverage and the outcomes of interest, such as road quality, landline coverage, donor funding, and private sector investment. Some of these factors, such as changing relations with France in the north and an increase in anti-terrorism activity, either occurred outside of our study sample (e.g., in the Saharan desert) or outside of our study period. Other changes occurring in Niger over this time (such as the introduction of Chinese investment into Niger in 2008 or increased aid in the wake of the 2005 food crisis) would need to be correlated with an increase in mobile phone rollout during our time period. Although Chinese investment could be a potentially important confounding factor, its importance increased during the 2007/2008, when most of the markets in our sample already had mobile phone coverage.

[19] Aker (2010) also included cross-border markets in the specification. This is not possible for producer prices because these data are not available from cross-border markets. Thus, all of the regressions using producer price data are only for markets within Niger.

[20] We also conducted the heterogeneity analysis by the market's landline status prior to mobile phone coverage and found no statistically significant effects. The results are available upon request.

[21] The Niger Agricultural Market Information System (AMIS) defines four different types of markets: producer, consumer, wholesale, and border. These categories are not mutually exclusive and are open to interpretation. Here, we regard as surplus markets those that are primarily classified as producer markets (i.e., those markets that are located in surplus regions and serve as major trading points for farmers to sell their produce).

[22] For the gross trade margin to change, consumer prices should fall, producer prices should rise, or both. The price that changes is akin to a standard tax incidence question: if the short-run price elasticity of demand is larger than the short-run price elasticity of supply, the average consumer price will fall by more than the average producer price rises. The demand for staple food is, in all likelihood, price inelastic. In contrast, supply may be more price elastic if farmers store their output or have alternative uses (e.g., cowpea cakes). Without independent evidence on short-run price elasticities in Niger, we are unable to make strong predictions either way. However, we expect no systematic effect on producer and consumer price differences within the same market because mobile phone coverage is unlikely to affect the spatial allocation of trade within a single market.

[23] The results in Columns 1 and 5 exclude cross-border markets (where consumer price data are available). The regression results are the same if consumer price data for cross-border markets are included (not shown).

[24] To answer this question precisely, we could use trader-level data on gross margins at different levels of the supply chain. Although we have trader-level data over a two-year period, we do not have these data over the full period of our sample.

[25]Restricting the sample to consumer price data during 1999–2007, we find that millet consumer prices decrease in deficit markets by 1.3-2.8 percent, with a statistically significant effect. The millet results are consistent with Aker (2008).

[26]This categorization is similarly true for a market's status as a collection, retail, or wholesale market, which is correlated with its categorization as surplus or deficit.

[27] There are only 411 observations in Panel A (Table 9) because the question was only asked of farmers who had sold the relevant commodities since the previous harvest (and thus could report a producer price). We did not impute the missing values with a zero price.

[28] Our results are also in contrast to Goyal (2010), who finds that internet kiosks increase producers' soybean prices in India. The technology is different from mobile phone coverage because it provides both price and quality information to farmers.

[29] Aker and Ksoll (2013) report similar findings: a mobile phone-based education intervention (which was randomized at the village level) occurring between 2009 and 2011 increased farmers' access to price information but did not change farmers' marketing behavior or the farm-gate price received.