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Jenny C. Aker, Tufts University
Marcel Fafchamps, University of Oxford and CEPR

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ABSTRACT

Mobile Phone Coverage and Producer Markets: Evidence from West Africa*

Expansion in mobile phone coverage has improved access to information throughout the developing world, particularly within sub-Saharan Africa. The existing evidence suggests that information technology has improved market efficiency and reduced consumer prices for certain commodities. There are fewer studies assessing the impact of the technology on producers. Using market-level data we estimate the impact of mobile phone coverage on producer prices in Niger. We find that mobile phone coverage reduced the spatial dispersion of producer prices by 6 percent for a semi-perishable commodity, cowpea. These effects are strongest for remote markets and lowest at harvest time. Mobile telephony, however, has no effect on price dispersion for millet and sorghum, two storable crops. There is also no impact on the average producer price, but mobile phone coverage is associated with a reduction in the intra-annual price risk, primarily for cowpeas. These findings are confirmed by data from a farmer-level survey: we find that farmers owning mobile phones obtain more price information but do not engage more in spatial arbitrage and hence do not receive higher prices – except for peanuts. The additional evidence presented here helps understand how mobile phone coverage affects agricultural market efficiency in developing countries. It suggests that the impact differs across agents – depending on whether they use the information for arbitrage or not – and across crops – depending on whether inter-temporal arbitrage is possible or not.

Jenny C. Aker
Department of Economics
Tufts University
University of California, Berkeley
160 Packard Avenue
Medford, MA 02155
USA

Email: jenny.aker@tufts.edu

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Marcel Fafchamps
Department of Economics
University of Oxford
Manor Road Building
Manor Road
Oxford
OX1 3UQ

Email:
mfafchamps@economics.ox.ac.uk

For further Discussion Papers by this author see:
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1. 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 on online databases (Autor 2001, Anderson and Magruder 2012). In sub-Saharan Africa, limited infrastructure has historically made obtaining information costly. Over the past decade, however, the spread of mobile telephony (Aker and Mbiti 2010) has enabled consumers and producers to send and receive information more quickly and cheaply. This paper examines how this has affected the spatial integration of agricultural markets in Niger.

In Niger farmers typically sell to traders, either by transporting their output to a local market or by waiting for traders to come and purchase it from their home village. Traders then sell the goods throughout the country. Between 2001 and 2008, mobile phone networks were introduced in Niger, with over 44 percent of the population having access to mobile phone service by 2008 (GSMA 2010). Even if service remained limited in the villages where most farmers live, by 2008 90 percent of local agricultural markets in our sample had mobile phone coverage. For farmers and traders, mobile phones reduced the cost of obtaining market information by 35-50 percent (Aker 2010).

We estimate the impact of mobile phone coverage on the spatial dispersion of producer prices and on producer price levels. We develop a simple model explaining how the circulation of information among traders is likely to improve spatial arbitrage. The model shows how, in the context of Niger, better circulation of information about local market conditions reduces the spatial dispersion of producer prices because it allows traders to reorient their purchases from high to low price markets. As local prices adjust, some farmers are hurt while others benefit – and hence the average producer price need not be affected. The model also predicts the spatial arbitrage effect to be strongest when intertemporal arbitrage is absent, as would be the case for perishable commodities.

Mobile telephony may affect agricultural prices in ways other than improving spatial arbitrage. Lower information costs may, with sufficient competition between traders, lead to a reduction in their gross margins, i.e., to a reduction in the average difference between producer and consumer price. Better

informed farmers may also reduce the monopsony power of traders, putting added downward pressure on trader margins. Because intertemporal arbitrage can smooth producer price fluctuations even in the absence of spatial arbitrage, we expect little or no effect of mobile telephony on gross margins for storable commodities, but a possible effect for perishables.

Reduced gross margins can translate into either higher producer prices or lower consumer prices. A straightforward application of tax incidence theory predicts that if supply is much more price elastic than demand, a reduction in the wedge between producer and consumer price results in a lower consumer price but leaves the producer price unchanged, and vice versa. Applied to our setting, this means that a reduction in trader gross margins may either lower consumer prices or increase producer prices, or both, depending on the relative elasticities of demand and supply.

We test these predictions using detailed information about producer prices in agricultural markets over time. To estimate the impact of mobile phone coverage on producer price dispersion, we use a difference-in-differences estimation strategy. We control for market-pair and monthly fixed effects and for variables that could be simultaneously correlated with mobile phone coverage and producer price dispersion. We also check for pre-treatment balance on observables and formally test the validity of the parallel trends assumptions.

Results suggest that mobile phone coverage reduced the spatial dispersion of producer prices by 6 percent for cowpeas, a semi-perishable commodity. We do not observe the same effect for millet or sorghum. However, we find heterogeneous effects, with larger effects for more isolated markets, during certain periods of the year, and for surplus markets. We do not find that mobile phones are associated with a reduction in gross margins for cowpea, millet or sorghum.

Next we investigate whether markets in which mobile telephony was introduced experienced an increase in producer prices relative to markets without mobile phone access. We find no evidence that mobile phone coverage translated into higher producer prices for either millet or cowpea, but reduced intra-annual price risk for cowpea by 6 percent. To explore this question further, we use a farmer survey to measure the impact of mobile phone ownership – rather than coverage – on prices received. Overall

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results are consistent with those from the market level data – except for peanuts where we find mobile phone ownership to be correlated with a positive and statistically significant increase in the price received by farmers. Unfortunately we do not have peanut price data at the market level.

We also use the farmer-level data to assess the impact on farmers' marketing behavior. Aker (2008) found prior evidence that improved access to information changes traders' search and arbitrage behavior. The analysis presented here indicates that mobile phone ownership is associated with better access to market information but does not significantly change farmers' marketing and arbitrage behavior and is not reflected in a higher price received. Using an experimental methodology, Fafchamps and Minten (2012) report similar findings for India.

This 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 empirical perspective (Autor 2001, Brown and Goolsbee 2002, Jensen 2007, Aker 2010, Goyal 2010). Recently some of this evidence has been extended to producer markets for commodities that are grown by a large percentage of farmers in the developing world (Goyal 2010, Fafchamps and Minten 2012, Muto and Yamano 2009). Yet few of those studies are able to assess the interaction between producer and consumer markets as we do in this study.

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) assess the relative impact of information technology on perishable and non-perishable commodities. Our study is not only able to look at price levels and market participation for multiple goods, but also at producer price dispersion over a long time period.[1]

The rest of this paper proceeds as follows. Section 2 provides an overview of the context and research design. Section 3 presents the theoretical framework. In Section 4 we present our data and Section 5 discusses the empirical strategy. Section 6 provides the main empirical results. Section 7 concludes.

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[1] In addition, having pre-treatment price data makes it possible to test the validity of the parallel trends assumption.

2. Context

2.1. Agricultural Markets in Niger

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 2010). Agriculture employs more than 80 percent of the total population and contributes approximately 41 percent to GDP (World Bank 2010). The majority of the population consists of subsistence farmers who depend upon rain-fed agriculture and livestock as their main source of food and income. The main grains cultivated are millet and sorghum. Cowpea is the primary cash crop and is primarily exported to Nigeria. Peanuts and sesame are grown as cash crops in some areas.

Millet and cowpea are produced by smallholders in the Sahelian and Sudano-Sahelian agro-climatic zones of Niger. Although both commodities can in principle be stored for several years, over 90 percent of farmers and traders in our study area do not engage in inter-annual storage. Unlike millet and sorghum, cowpea is highly susceptible to pests during storage and is considered semi-perishable.

A variety of market intermediaries are involved in taking agricultural commodities from producers to rural and urban consumers. Small-scale farmers typically sell their agricultural products to traders in their village or in a nearby market. Traders then sell to wholesalers in local markets, who in turn sell to buyers (wholesalers, retailers or consumers) in regional markets. As there is only one rainfed harvest per year, traders and farmers engage in intra-annual storage but seldom store for more than a year (Aker 2008).

Trade in agricultural commodities takes place through a system of weekly markets. Across all of Niger, the average distance between any pair of markets is 350 km. Farmers are located on average 7.5 km away from the closest weekly market. While 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 and professional networks.[2]

2.2. Rollout of Mobile Phone Coverage

Mobile phone service was first introduced in Niger in October 2001. Three private mobile phone operators (Celtel, Sahelcom and Telecel) originally intended to provide universal coverage by 2009, but mobile phone service was introduced gradually. At the outset, mobile phone operators prioritized urban centers and proximity to international borders.[3] 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. Coverage and subscribers 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. Most of the increase in coverage into 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 2 landlines available per 1,000 people compared to 113 landlines per 1,000 people in South Africa (World Bank 2005). The number of landlines remained relatively stable during this period (Figure 2).[4] 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 still 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 (Wireless Intelligence 2009). Mobile phones were first adopted by urban residents and traders, who were more likely to afford a handset. A trader survey conducted in 2006 shows that 32

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[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 due to the type of data (only consumer prices are provided) and the timing of the data diffusion (the data is provided weekly, in some cases six days after a market).

[3]Based upon 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.

percent of them owned a mobile phone and used it for their trading operations. In contrast, less than 5 percent of farm households owned a mobile phone at that time.[5]

3. Conceptual Framework

To clarify how we expect mobile telephony to affect spatial integration of producer prices, we present a model of weekly agricultural markets visited by farmers and itinerant traders. The model is based on a fair albeit stylized description of how agricultural traders operate in this part of the world (Fafchamps, Gabre-Madhin and Minten 2005).

Because each market operates for a few hours and markets are far apart, it is difficult if not impossible for farmers or traders to visit more than one market in a given day. In the absence of mobile phones, farmers and traders must therefore physically visit one market in a given day to obtain price information. Farmers travel on average 1.5 hours to reach the nearest market, a significant cost in terms of time and transport.[6] For this reason, they sell their output either at the farm-gate or at the market nearest to them. Farmers who bring output to the market are reluctant to carry it back home to sell later because of the cost of doing so. Hence supply on any given market day is inelastic. Since each weekly market serves a large area, farmers cannot coordinate supply. Consequently supply varies randomly across market days in ways that traders cannot predict. This is what generates potential gain from spatial arbitrage if better informed traders can select which market to visit depending on local supply.

Mobile telephony reduced the cost of obtaining information about local market conditions. In Niger the cost of obtaining price information from a market located 10 km away fell by 35-50 percent between 2001 and 2008 – more for markets further away.[7] This reduction affected traders more than farmers because mobile phone coverage reached most small towns (where most traders reside) and many weekly markets first, but did not expand significantly into rural areas until after 2008.

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[5] Since 2008, mobile phone coverage and adoption has 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] Agricultural traders in Niger also typically relied upon personal travel to obtain price information prior to the introduction of mobile phones.
[7] In 2008, a two-minute call to a market located 10 km away cost US$.50, as compared to US$1 for roundtrip travel using a market truck or cart.

We now present a model capturing these different features in a stylized way, and we use it to illustrate how mobile telephony can increase spatial arbitrage and reduce price dispersion while keeping the average producer price unaffected.

3.1. The Model

To keep things in 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.[8] 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 consumer 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[9] and is known to traders, but the exact quantity on each market is unknown. 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.[10] 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 therefore follows that the variance of $\tilde{d}_m$ increases in n, the number of markets from which traders must choose.

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:

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

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[8] 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.

[9] 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.

[10] We only consider symmetric equilibria (thereby 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.

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:

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

which is increasing in the number of producers who brought their produce to the market that day, and decreasing in the number of traders who chose market n.

In the absence of temporal arbitrage, the 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:

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

As 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 $\tilde{d}_m$. Thus, a trader could benefit from obtaining an informative signal about the realization of $\tilde{q}_m$ or $\tilde{d}_m$. Without this signal, the best response function of the trader is:

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

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 $\tilde{q}_m$ since 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:

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

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

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

Given symmetry, it follows that $\pi_m = \hat{\pi}_m = \frac{1}{n}$: 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.

3.2. Informative Signals

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

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

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:

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

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:

$$(9) \qquad r\bar{q}_s\bar{C} = r\bar{q}\bar{C}, s.t. \bar{q}_s = \bar{q}$$

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

$$(10) \qquad \pi_s = 1 \ if \ \bar{q}_s > \bar{q} \ and \ \pi_s = 0 \ if \ \bar{q}_s < \bar{q}$$

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 markets, increase the price in that market, and abandons small surplus markets, reducing demand and price there. Since small surplus markets have a high price and large surplus markets have a low price, the action of the informed trader reduces the price difference between high and low surplus markets.

We now show that 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

made of one consumer market and n supply markets. We now have $F(\hat{d}_s) \neq F(\hat{d}_m)$. First note that, if $\frac{\bar{q}_s}{n} = \bar{q}\bar{C}$, the signal in favor of market s is very strong and we get 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:

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

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:

$$(12) \qquad \theta \equiv \bar{q}_s/\bar{q} = E\left[\frac{1}{1+\hat{d}_i}\right]/E\left[\frac{1}{1+\hat{d}_s}\Big|s\right]$$

where θ represents the strength of the signal.

By symmetry, all traders face the same decision problem and thus their π_s will all be the same:

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

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

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, $\partial\pi_s/\partial\theta > 0$: the more positive the signal, the higher the probability that traders visit market s. This raises prices in large surplus/low price markets and lowers them in small surplus/high price markets, thereby reducing price dispersion.

3.3. 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 use by farmers. The model

suggests that the introduction of mobile telephony 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 large surplus/low price markets and lower them in small surplus/high price markets; and 3) reduce spatial price dispersion between markets with mobile phone coverage.

These effects need not be present for storable commodities. This is because intertemporal arbitrage sets a ceiling or a floor on the price at which producers and traders are willing to trade, and can thus reduce price dispersion even in the absence of informative signals.[11] This implies that the predictions above apply to perishable and semi-perishable commodities, but not necessarily to non-perishables. In rest of this paper we formally test the second and third hypotheses and provide suggestive evidence in support of the first, and we contrast test results across a non-perishable and a semi-perishable commodity.

4. Data and Summary Statistics

In this paper we use 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. A producer price observation is the average price that farmers received for selling a given crop in that market during that month. 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 distance and road quality between pairs of markets.[12] These data are further combined with information – obtained from the three mobile phone service providers – on the location and date of mobile phone coverage in each market between 2001 and 2008.

The second dataset is a panel survey of traders and farmers interviewed in Niger between 2005 and 2006. The survey includes 415 traders and farmers in 35 markets and associated villages across 6

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[11] To illustrate in 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 p_m because few traders happen to visit market m on that day. Rather than selling at low price p_m, 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.

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

geographic regions of Niger. Table A1 provides summary statistics of traders' characteristics. We see that 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 4 markets. Traders have an average of 16 years' of trading experience, and only 10 percent changed their market since they began trading. Table 1A provides summary statistics for farmers. Despite low levels of production, on average 25 percent of farmers sell millet and 75 percent sell cowpeas. Compared to traders, farmers trade over a smaller geographic area: they sell in 1.46 markets, and search for price information in 1.5 markets.

Fewer than 5 percent of the villages in the farmer sample had mobile phone coverage between 2005 and 2006, with similarly low mobile phone adoption. This means that inferences drawn from the producer-level data have low power. We therefore rely upon a survey of 1,038 farm households from 100 Niger villages in 2009. The survey collected data on agricultural production and marketing behavior, as well as mobile phone coverage and ownership in each village. While the survey is only a cross-section, it provides insights into the relationship between mobile phone coverage and farmers' prices, access to information and marketing behavior. Table 1B provides summary statistics for farm households. Overall many of the socio-demographic indicators are similar; households have low levels of education, are primarily from the Hausa ethnic group and households have eight household members. Approximately 30 percent of households owned mobile phones. Millet and cowpea are the primary crops grown by farm households in our sample, followed by sorghum and peanut. Over 70 percent of households had sold cowpea since the previous harvest, as compared with 36 percent of households who sold millet. Farm households purchased and sold their grain and cash crops in 2.3 markets, and primarily sold to traders located in markets.

5. Empirical Strategy

5.1. Core Specification

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

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

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.[13] $mobile_{jk,t}$ is a binary variable equal to one in month t if both markets j and k have mobile phone coverage, and 0 otherwise.[14] The α_{jk}'s are market-pair fixed effects; they control for geographic location, urban status and market size. The θ_t's are a vector of yearly or monthly time dummies. 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.[15] The parameter of interest is β_1: a negative value indicates that mobile phone coverage reduces price dispersion between markets pairs.

As 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 market pair. 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).

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

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[13]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 also use the CV and the max-min as alternative specifications.

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

[15] 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% of markets received some type of road improvement between 1999 and 2008, with the majority of this improvement occurring in 2007/2008, towards the end of our sample period and well after mobile phone coverage was introduced into these markets.

(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 at month t.

5.2. Identification and Assumptions

To interpret β_1 as identifying 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. First we examine whether mobile phone coverage during our study period expanded primarily in isolated agricultural markets for which the potential for secular improvement in market integration was the greatest. This does not appear to be the case. Mobile phone operators interviewed about the determinants of tower placement during our study period cite two main considerations: whether a location was in or near an urban center with more than 35,000 people; and whether it is near the border with Benin, Burkina Faso or Nigeria. To verify these claims, we regress 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). Regression results confirm the interviews with mobile phone operators (Table 2): urban areas were more likely to receive mobile coverage, as were markets with paved roads, a variable correlated with urban status (Column 1). The eastern part of the country with more border markets was also more likely to receive mobile phone coverage earlier. Characteristics 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 was 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 check whether this is the case, Table 3 shows 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 treated and untreated 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 earlier results. While pre-treatment differences in producer price levels and price dispersion for millet are not statistically different from zero, there is a statistically significant difference in pre-treatment cowpea producer prices and producer price dispersion. There are two things to note about this finding. First, the statistically significant difference only exists for one of the two pre-treatment years, rather than both, suggesting that this was not systematic. And second, we note that pre-treatment price dispersion for cowpea is, if anything, lower in non-mobile phone markets. Hence, if our findings are biased due to non-random placement of phone towers, it probably is 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 might be violated if we are not controlling 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 treated and untreated markets follow different time trends, this should already be apparent before treatment began. We find that the pre-intervention trends for the log of cowpea producer prices (Column 3) and cowpea producer price dispersion (Column 4) are not statistically different from zero for markets and market pairs that received mobile phone coverage. There seems to be somewhat differing trends for millet producer prices (Column 1) and producer price dispersion (Column 2). This raises some concerns regarding the parallel trend assumption for millet producer price dispersion. Nevertheless, mobile phone

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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, it is important to note that these findings are primarily driven by one of the pre-treatment years, rather than both.

6. Results

In this subsection we present the results by commodity, using different dependent variables. We then present heterogeneous treatment effects, breaking down the mobile phone effect by distance, road quality, season and type of market. We end with an assessment of the impact mobile phone coverage on producer-consumer margins and producer price levels.

6.1. Average Effects of Mobile Phone Coverage on Producer Price Dispersion

Table 5 presents the regression results of equation (15) for cowpea (Columns 1-4) and millet (Columns 5-8). As explained in section 3, we expect mobile phone coverage to reduce price dispersion for cowpea more than for millet or sorghum, as cowpea is a semi-perishable commodity. We look at cowpea first. Controlling for yearly, monthly and market pair fixed effects (Column 1), we find that mobile phone coverage reduces producer price dispersion for cowpeas by 6.3 percent. These results are robust to the introduction of additional covariates that also affect producer price dispersion across markets (Column 2), such as drought and transport costs. The results are similar when including market fixed effects with the standard errors clustered by quarter (Column 3). We also redefine the treatment by including a dummy 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, reducing producer price dispersion across markets by 7 percent. 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 as compared to market pairs without mobile phones in the pre-treatment period.[16]

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

Columns 5 to 8 contain similar regressions for millet. Mobile phone coverage reduces millet producer price dispersion across markets by as little as 0.1 percent. The magnitude and statistical significance of this effect is similar across all specifications (Columns 5-8). Equation (15) was also estimated for sorghum, the second staple grain in Niger. Like millet, sorghum is storable.[17] Results for sorghum mirror those for millet. Taken together, these results are consistent with the idea that, for non-perishable commodities such as millet and sorghum, stock markets act as a buffer on local market price fluctuations, keeping prices aligned across producer markets even in the absence of market information. The results also suggest that grain stocks are held in or near producer markets.

A concern with the price data is the presence of missing observations. Since demand for staple grains is relatively constant throughout the year, consumer price data are readily available for each market and each month (Aker 2010). By 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, e.g., during the hungry season prior to the annual harvest.

To check the robustness of our cowpea results to 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 (Table A2), and adding the resulting inverse Mills' ratio as a separate regressor to equation (15). Results are presented in Table A3 (columns 1-4). Results 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 A3, columns 5-8). We get slightly smaller point estimates – a 4% reduction in price dispersion – but coefficient estimates remain significant at the 1 percent level.

The results for millet *producer* prices presented here differ from 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

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[17] Because sorghum requires more rainfall and Niger is predominantly dry, sorghum price data are available for fewer markets and during fewer periods of year. For this reason, results are not shown here to save space.

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 rapidly know 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) that uses a measure of producer price dispersion similar to those used by Jensen (2007), the max-min producer price spread (in CFA/kg) of markets across a region. The independent variable of interest is the intensity of mobile phone coverage within a region, rather than the mobile phone coverage 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 (not shown). While the interpretation of equation (16) is not directly comparable to (15), results in Table 6 demonstrate that our findings are not an artifact of the dyadic specification.

6.2.   Heterogeneous Effects of Mobile Phone Coverage

From the model presented in Section 3, the effect of mobile phone coverage on producer price dispersion is predicted to be larger for markets and time periods when access to information reduces the spatial misallocation of traders across markets. We expect coordination failure among traders to be strongest when search costs are high, that is, when markets are distant and transport costs are large, e.g., because of poor road quality. In addition, supply shocks and trader miscoordination are expected to be highest – and benefits from mobile phones largest – at times of the year when markets are thin, i.e., outside of the harvest period when most farmer sales take place. Heterogeneous effects by market type – surplus or deficit – depend upon the commodity. For semi-perishable crops, both deficit and surplus markets experience shocks that cannot be smoothed out by storage, and thus benefit from better spatial arbitrage. For non-perishable crops such as millet, inter-temporal arbitrage through storage reduces the potential benefits from spatial arbitrage. In Niger grain storage is believed to be undertaken

predominantly by farmers and traders residing in the vicinity of surplus markets. In contrast, little storage is believed to take place in deficit markets. For millet, we expect that mobile phone coverage might reduce price variation primarily in deficit markets where it is not mitigated by storage.

Table 7 estimates the effect of mobile phone coverage by distance, road quality, season, and whether the market is in surplus or deficit.[18] The regressions are similar to those in Columns 3 and 7 of Table 5, except that they include an interaction term between mobile phone coverage and the heterogeneous effect of interest. Columns 1 to 5 focus on cowpea. Column 1 includes the interaction between mobile phone coverage and a binary variable equal to one if markets are more than 350 km apart. Consistent with model 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. Consistent with theoretical predictions, the coefficient is positive, suggesting that mobile phone coverage has a greater impact on markets that are linked by unpaved roads (a 7 percent reduction) as compared with paved roads (a 6 percent reduction). But, this difference is not statistically significant at conventional levels. Column 3 introduces an interaction term between mobile phone coverage and the harvest period. The coefficient on the interaction term is positive and statistically significant, suggesting that mobile phone coverage reduces producer price dispersion *less* at harvest than during other seasons, again in agreement to theoretical predictions. Finally, Columns 4 and 5 introduce an interaction term between mobile phone coverage and "surplus" markets, which are defined as those markets that are primarily production markets for most of the year.[19] In Column 4, the surplus variable is equal to one if both markets in a pair are surplus markets, 0 otherwise; in Column 5, the variable is equal to one if one

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

[19] 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 producer 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.

market is a surplus market, the other a deficit market.[20] Coefficient estimates are negative, suggesting that the reduction in price dispersion is stronger in producer markets. The magnitude of the effect is small, however, and not significant in Column 5.

We find similar results for millet – see columns 6-10. 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, even 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 surplus market dummies. Results are inconclusive: coefficient estimates are negative (and contrary to theoretical expectations) in column 9 but positive in column 10.

6.3. Impact on Gross Trade Margins and Producer Prices

We next examine the impact of mobile phone coverage on producer-consumer margins and price levels. By reducing miscoordination among traders, improved information flows are expected reduce traders' costs. With sufficient competition among traders, this should reduce the average gross trade margin, that is, the difference between average consumer and producer prices: the consumer price should fall or the producer price should rise – or both.[21] This effect operates only on gross trade margins affected by mobile telephony. Hence it should only affect price differences between geographically distinct

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[20]Alternatively, we can define the surplus variable as being equal to one if one market is surplus and one market is deficit.

[21] Asking which price – consumer and producer – changes most 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 probably price inelastic. In contrast, supply may be more price elastic if producers store their output or have alternative uses (e.g., cowpea cakes). Without independent evidence on short-run price elasticities in Niger, however, we cannot make strong predictions either way.

surplus and deficit markets – such as rural producer markets and urban consumer markets.[22] Aker (2008) found that mobile phone coverage was associated with a decrease in consumer prices between 2001 and 2006. Whether mobile phone coverage increased producer prices remains an empirical issue.

To investigate whether mobile phone coverage affected gross trade margins, we estimate equation (15) using as dependent variable the difference in logged consumer prices in market j (a deficit market) and logged producer prices in market k (a surplus market), using only market pairs a deficit and a surplus market. Here β_1 measures the percentage reduction in gross trade margin associated with the introduction of mobile phone coverage in both markets.

Following Goyal (2010), we also estimate the effect of mobile telephony on producer prices, as well as intra-annual price variation within each market. The estimated equation is:

$$(17) \qquad Y_{j,t}^i = \beta_0 + \beta_1 mobile_{j,t} + X_{j,t}'\gamma + \alpha_j + \theta_t + \mu_{j,t}$$

with three different dependent variables $Y_{j,t}^i$: (1) the log of producer price in surplus market j in month t; (2) the log of consumer price in deficit market j in month t; and (3) the intra-annual coefficient of variation of commodity i on market j at year t. $mobile_{j,t}$ is a dummy equal to one at time 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 α_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, depending on whether the dependent variable varies by month or year) that control for time-varying aggregate factors. Standard errors are clustered at the market level.

Results are presented in Table 8. Columns 1-4 relate to cowpeas, columns 5-8 to millet. Columns 1 and 5 report dyadic regression results documenting the average effect of mobile phone coverage on the gross trade margin between deficit and surplus markets.[23] We find no significant coefficient for either cowpea or millet, suggesting that the efficiency gain from better spatial arbitrage was not large enough to

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[22] We expect no systematic effect on producer and consumer price differences within the same market since mobile telephony is unlikely to affect the spatial allocation of trade within a single physical 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).

be reflected in the average gross margin between surplus and deficit markets. The rest of Table 8 presents regression results for equation (17). We find no effect on the average producer price in surplus markets for either cowpea (Column 2) or millet (Column 6). For deficit markets, we do not find any statistically significant effects of mobile phone coverage on consumer prices in deficit markets for either cowpea (Column 3) or millet (Column 7). If we use data from 1999-2007, we find that millet consumer prices decrease in surplus markets by 1.3-2.8 percent, with a statistically significant effect, but no effect for cowpea. The millet results are consistent with Aker (2008). One possible explanation for the lack of results is that the categorization of markets into surplus and deficit is imperfect: whether a market is in surplus or deficit varies across years and seasons, but with no information on trade flows we are forced to use a categorization based on average trade patterns.

Finally, we also estimate equation (17) using the intra-annual coefficient of variation as 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 intra-annual price risk for cowpea farmers in Niger. For millet we find a negative but not statistically significant effect (Column 8). These findings are consistent with model predictions.[24]

A limitation of the market-level data is that while markets had mobile phone coverage, mobile phone coverage at the village level was still relatively new by 2008. After that date, mobile phone coverage could, in theory, have become more favorable to farmers. To gain more insights into this question, we use a farm household survey collected 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 and 30 percent of farmers owned mobile phones. There are obvious limitations in using a cross-sectional

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[24] Prior to the introduction of mobile phones, producers faced an intra-annual distribution of prices. Once mobile phones were introduced, this distribution shifted, as is depicted in Figure 3. This implies that risk-averse, expected profit-maximizing producers would prefer the distribution of prices under mobile phone coverage, assuming that farmers are net sellers.

survey to study impact. Still, the data provide useful insights into the micro-foundations of the market-level data.

Our dependent variables of interest are 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:

$$(18) \qquad Y_j^i = \beta_0 + \beta_1 mobileown_j + X_j'\gamma + \alpha_k + \mu_{jk}$$

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 price received unless they can use this information for arbitrage – e.g., by changing the timing of sales (something that is only possible for non-perishable crops) or by switching sales market. We realize that β_1 may be biased upward if phone ownership is correlated with time-varying unobserved factors, such as motivation or intrinsic marketing ability. But if we find that β_1 is not different from zero, this bias should not affect inference.

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).[25] 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. But they stand in contrast to Jensen (2007) and Goyal (2010) who find that information technology increases producer prices. These differences may have a logical explanation, though. Jensen examines what happens when fishermen at sea use mobile phones to obtain price information and decide in which port to land their fish, a context where producers have a comparative advantage in spatial arbitrage and mobile phones facilitate such arbitrage. Goyal assesses the impact of internet kiosks on soybean prices in India. The technology is

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[25] 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.

different from ours because it facilitates coordination among farmers and it provides information on prices as well as quality-checking.

6.4.   Information Acquisition and Arbitrage Behavior

To confirm our interpretation of the findings, we look for direct evidence of information acquisition and arbitraging behavior. We have argued that mobile phone coverage improve *traders'* access to information on producer prices in different markets, thereby facilitating their spatial arbitrage. Has direct evidence of this been found? Second, mobile telephony may improve *farmers'* access to information, thereby allowing them in principle to engage in spatial arbitrage, either between markets, or between farm-gate and market sales. What evidence is there of such arbitrage by farmers?

Regarding the first question, Aker and Tack (2012) find evidence that, in Niger, mobile phone coverage increased traders' access to information and changed their search and marketing behavior. Using a trader-level dataset, they find that mobile phone coverage is associated with an increase in the number of search markets traders use, and in the number of people they contact for price information. The effect is driven by the duration of mobile phone coverage. Mobile phone coverage is also associated with a change in arbitrage behavior: traders in mobile phone markets increase by 25 percent the number of markets where they buy and sell agricultural commodities. 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 (Aker 2010).

To address the second question, Table 9 (Panel B) provides some initial evidence of the impact of mobile phone coverage on farmers' behavior, using a specification similar to equation (18). We find that the introduction of mobile phone coverage 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. But unlike traders, farmers do not increase the number of markets at which they search for price information, and similar to Fafchamps and Minten (2012) they do not change their marketing behavior. Aker and Ksoll (2012) 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 it did not change farmers' marketing behavior or the farm-gate price received. This confirms that, despite increased access to information, farmers in these countries do not appear to engage in spatial arbitrage.

7. 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 analysis, it reduced the spatial dispersion of producer prices for cowpeas, a semi-perishable crop. But it did not affect spatial price dispersion for millet or sorghum, two storable grains. We also find a stronger reduction in dispersion in remote markets and away from the harvest season. The reduction in price dispersion, however, did not increase the average price received by farmers even though it reduced the intra-annual price risk, primarily for cowpeas.

This paper provides empirical evidence of the importance of informative signals for market efficiency, and the differential impacts by crop and by market agent. These results, combined with those in Aker (2010) and Aker and Tack (2012), indicate that the introduction of mobile phones has generated net efficiency gains in Niger. We however found no evidence suggesting that these gains have translated into higher average prices for the primary suppliers of these commodities – although we did find a reduction in intra-annual price variation in producer markets.

These findings are central to the current debate on the role of information technology in promoting economic development. Information technology is often considered to be a low development priority. Yet some believe that, by reducing communication costs over long distances, mobile phones can serve to reduce poverty among rural households. The results presented here demonstrate that the impact of the technology can differ substantially by the type of crop (semi-perishable or storable), the type of agent (consumer, trader, or producer), and the time of year, even within the same country. Differences in impact can be linked to differences in arbitrage opportunities and market behavior between agents. We also suspect that differences in price elasticity between supply and demand would affect the distribution

of efficiency gains between consumers and producers, although we were unable to provide evidence on this issue.

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Figure 1. Mobile Phone Coverage by Market and Year, 2001-2008
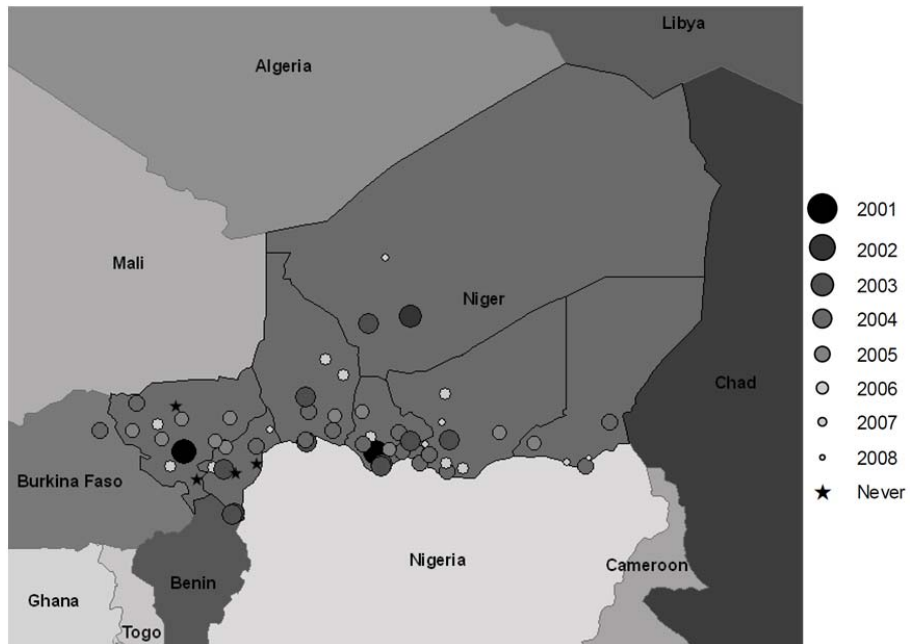
Notes: Data collected from the mobile phone companies in Niger (Zain/Airtel, Moov and Sahelcom). The map shows mobile phone coverage for grain markets between 2001 and 2008.

Figure 2. Mobile Phone Subscribers, Landlines and Road Quality, 2001-2008
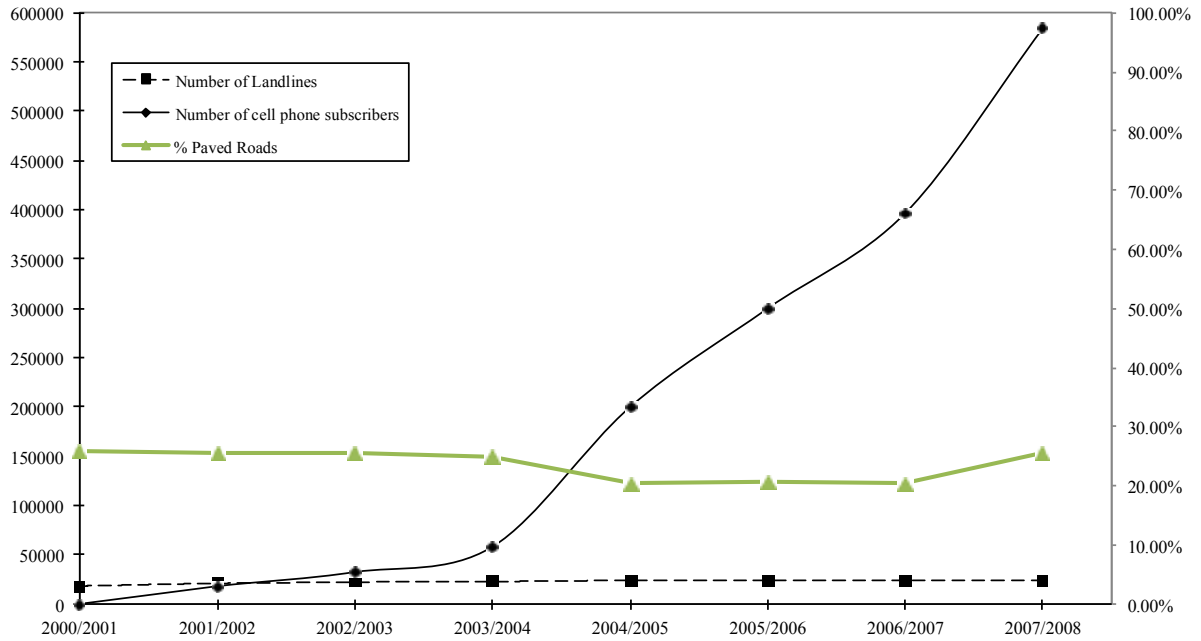
Notes: Raw data obtained from Sonatel/Niger (number of landlines), Wireless Intelligence (number of mobile phone subscribers) and the World Bank (http://data.worldbank.org/country/niger).

Figure 3. Distribution of Farm-Gate Cowpea Prices by Treatment Status

Kernel density estimate

kernel = epanechnikov, bandwidth = 7.99
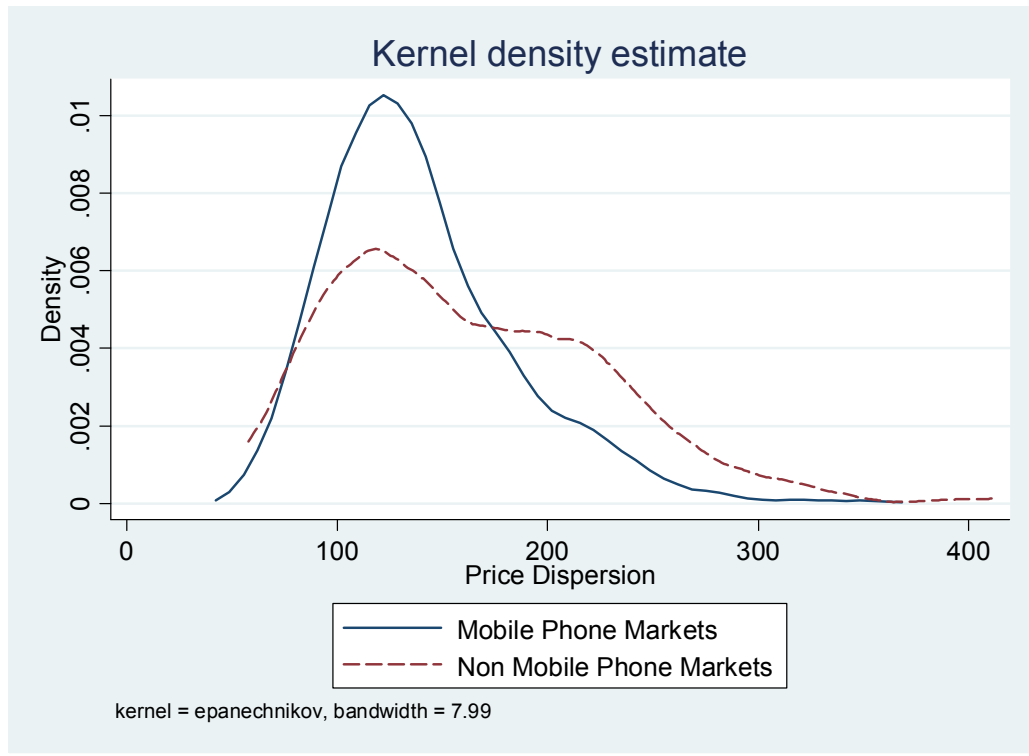
Table 1A. Farm Household Summary Statistics 2005-2007

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 sell product	0.64
Household follows market price information	
Personal conversations with traders and farmers	0.75
Radio (MIS)	0.09
Other	0.14

Notes: Data from the farmer survey in Niger collected between 2005 and 2006. Sample means are weighted by inverse sampling probabilities. Total sample size is 200 farmers across 37 villages in 2005 and 2006. Respondents were primarily the household head.

Table 1B. Farm Household Summary Statistics 2009

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 the previous harvest	.35 (.48)
Purchased sorghum since the previous harvest	.12 (.32)
Purchased cowpea since the previous harvest	.11 (.32)
Purchased peanut since the 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)

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

Table 2. Determinants of Mobile Phone Coverage in Niger

Dependent variable: Mobile phone coverage 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

Notes: Data collected from the mobile phone companies in Niger between 2001-2008. Mobile phone coverage is equal to 1 in market j at time t if the market received mobile phone coverage, 0 otherwise. The slope dummy is equal to 1 if the market is steeply sloped, 0 otherwise. Urban center is equal to 1 if the market has a population greater than 35,000 people, 0 otherwise. Road quality is equal to 1 if the market has access to a paved road, 0 otherwise. Column 1 is OLS estimation, Column 2 is probit estimation. *** statistically significant at the 1 percent level, ** at the 5 percent level, * at the 10 percent level.

Table 3. Comparison of Observables by Mobile Phone Coverage in the Pre-Treatment Period (1999-2001)

	Unconditional Mean		Difference in Means
	(1)	(2)	(3)
	Mobile Phone Mean (s.d.)	**No Mobile Phone 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)
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)	0.17	0.13	0.04
	(0.15)	(0.13)	(0.03)
Ln (Cowpea Producer price dispersion)	0.22	0.17	0.05***
	(0.18)	(0.14)	(0.02)
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)

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

Table 4. Differences in Pre-Treatment Producer Price Trends by Treatment Period

	Millet		Cowpea	
	(1)	(2)	(3)	(4)
Dependent Variable	$ln(P_{jt})$ Coef. (s.e.).	$\|ln(P_{jt})-ln(P_{kt})\|$ Coef. (s.e.).	$ln(P_{jt})$ Coef. (s.e.).	$\|ln(P_{jt})-ln(P_{kt})\|$ Coef. (s.e.).
Mobile phone market*time	-0.08**	0.04***	-0.01	-0.02
	(0.03)	(0.01)	(0.04)	(0.02)
Time (=1 if 2000/2001, 0 if 1999/2000)	0.56***	-0.04***	0.09*	-0.09***
	(0.04)	(0.00)	(0.04)	(0.02)
Market fixed effects	Yes	No	Yes	No
Market pair fixed effects	No	Yes	No	Yes
Additional covariates	Yes	Yes	Yes	Yes
R^2	0.86	0.08	0.73	0.12
Number of observations	423	7190	408	6696

Notes: Data from the Agricultural Market Information Services (AMIS) and mobile phone service providers in Niger. Huber-White robust standard errors clustered by market (Columns 1 and 3) or market pair (Columns 2 and 4) are in parentheses. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are in 2001 CFA.

Table 5. Impact of Mobile Phones on Cowpea and Millet Producer Price Dispersion

Dependent variable: $|ln(P_{it})-ln(P_{kt})|$	Cowpea				Millet			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile coverage both markets	-0.06***	-0.06***	-0.06***	-0.08***	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Mobile coverage one market				-0.01***				-0.00
				(0.00)				(0.00)
Other covariates	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Market pair fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Market pair-specific time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	39120	39120	39120	39120	39002	39002	39002	39002
R-squared	0.154	0.165	0.37	0.38	0.09	0.09	0.32	0.32

Notes: Data from the Niger trader survey and secondary sources collected by one of the authors. For market pairs, mobile phone coverage = 1 in period t when both markets have mobile phone coverage, 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 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

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

	Cowpea	Millet
Dependent variable: Max-Min Price Spread (CFA) within a Region	**(1)**	**(2)**
Percentage of markets with mobile phone coverage in region j at time t	-36.90**	2.06
	(9.40)	(3.08)
Additional covariates	No	No
Year fixed effects	Yes	Yes
Monthly fixed effects	Yes	Yes
Market fixed effects	Yes	Yes
Number of observations	3107	3029
R-squared	0.42	0.36

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. *** denotes significant at 1 percent level, ** denotes significant at .05 percent level and * denotes significant at .10 percent

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

	Cowpea					Millet				
Dependent variable: $|ln(P_{it}\text{-})\text{-}ln(P_{jt})|$	(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	No
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

Notes: Data from the Niger trader survey and secondary sources collected by one of the authors. Each column is a separate regression. For market pairs, mobile phone coverage = 1 in period t when both markets have mobile phone coverage, 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 parentheses. All prices are deflated by the Nigerien Consumer Price Index (CPI). Includes data for market pairs within 900 km of each other. *** significant at 1 percent level, ** significant at the 5 percent level, * significant at the 10 percent level.

Table 8. Impact of Mobile Phones on Gross Margins, Producer Prices and Consumer Prices

Dependent variable:	Cowpea				Millet			
	$ln(PC_{jt})-$ $ln(PP_{kt})$	$ln(P_{jt})$	$ln(C_{jt})$	Intra-annual CV	$ln(P_{jt})-$ $ln(PP_{kt})$	$ln(P_{jt})$	$ln(C_{jt})$	Intra-annual CV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mobile phone coverage	0.01	0.00	0.018	-0.06***	-0.00	-0.00	-0.005	-0.02
	(0.01)	(0.02)	(0.013)	(0.02)	(0.01)	(0.01)	(0.008)	(0.02)
Other covariates	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Market pair fixed effects	Yes	No	No	Yes	Yes	No	No	Yes
Market fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market-specific time trend	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Cross-border markets	No	No	No	No	Yes	No	No	No
Number of observations	28035	1,193	1861	3033	27958	1,153	1875	2958
R-squared	0.52	0.84	0.74	0.44	0.60	0.89	0.86	0.55

Notes: Data from the Niger trader survey and secondary sources collected by one of the authors. For market pairs, mobile phone coverage = 1 in period t when both markets have mobile phone coverage, 0 otherwise. Columns 1 and 5 is the difference in log consumer prices in deficit markets and producer prices in surplus markets. Columns 2 and 6 are the log of producer prices in surplus markets, and Columns 3 and 7 are the log of consumer prices in deficit markets. Additional covariates include the presence of drought in both markets at time t. Huber-White robust standard errors clustered by market pair are in parentheses. All prices are deflated by the Nigerien Consumer Price Index (CPI). *** significant at 1 percent level, ** 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) Mean of Non-Mobile Phone Households	(2) Mobile-Non-Mobile Owners
Panel A: Producer Prices		Coeff (s.e.)
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	

Notes: Data from a farm household survey collected for Project ABC in 2009 (Aker and Ksoll 2012). The total sample size is 1,038 farm households across 100 villages in Niger. Respondents were either men or women within the household who were 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.   * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level.