Information from Markets Near and Far: Information Technology, Search Costs and Grain Markets

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Abstract. Due partly to costly information, price dispersion across markets is common in developed and developing countries. Between 2001 and 2006, cell phone service was phased in throughout Niger, providing an alternative and cheaper search technology to traders and other market actors. I construct a novel theoretical model of sequential search, in which traders engage in optimal search for the maximum sales price, net transport costs. The model predicts that cell phones will increase traders' reservation sales prices and the number of markets over which they search, leading to a reduction in price dispersion across markets. Using a new market and trader dataset that combines data on prices, transport costs, rainfall and grain production with cell phone access and trader behavior, I provide empirical estimates of the impact of cell phones on grain market performance in Niger. The results provide evidence that cell phones reduce grain price dispersion across markets by a minimum of 6.4 percent and reduce intra-annual price variation by 12 percent. Cell phones have a greater impact on price dispersion for market pairs that are farther away, and for those with lower road quality. This effect becomes larger as a higher percentage of markets have cell phone coverage. The primary mechanism by which cell phones affect market-level outcomes is a reduction in search costs: traders operating in cell phone markets search over a greater number of markets and sell in more markets. The results suggest that cell phones improved consumer and trader welfare in Niger. The findings provide novel evidence on the mechanisms through which information technology affects markets in a developing country context. (*JEL* O1, O3, Q13)

Key words: Information, Information Technology, Market Performance, Search Costs, Africa.

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"[With a cell phone], in record time, I have all sorts of information from markets near and far…"
Grain trader in Magaria, Niger[1]

1. Introduction

Economic theory relies heavily upon the assumption that market agents have the necessary information to engage in optimal arbitrage, and that this information is symmetric. In reality, however, information is rarely costless or symmetric. Due partly to costly information, excess price dispersion across markets is a common occurrence (Stigler 1961, Brown and Goolsbee 2002) and is especially acute in developing countries (Jensen 2007). In this context, a new search technology can have important implications for search behavior and hence the performance of nascent markets.

This paper estimates the impact of a new search technology – cell phones -- on dispersion in grain prices in one of the world's poorest countries, Niger. Between 2001-2006, cell phone service was phased-in throughout Niger, a landlocked country located in West Africa. Grains (primarily millet) are central to producer and consumer welfare,[2] and are bought and sold through an extensive system of markets that run the length of the country. Traders have traditionally traveled long distances to potential sales markets to obtain market information. Given the high costs associated with personal travel, cell phones should be able to reduce traders' marginal search costs, thereby allowing them to search over a larger number of markets more quickly. This fact is supported by the grain traders themselves, one of whom stated, "[With a cell phone], I know the price for US$2, rather than traveling (to the market), which costs US$20."[3]

Since Stigler's seminal work on the "Economics of Information", a large literature on consumer search theory has emerged, in an effort to explain how changes in search costs affect market actors' behavior and equilibrium price dispersion. To determine how the introduction of cell

[1]Based upon interviews with the author during the 2006 Niger trader survey.
[2]Millet is produced in almost every agro-ecological zone of Niger and represents over 70 percent of daily caloric consumption (INS 2005).
[3]Based upon interviews with the author during the trader survey of 2006. By 2006, 29 percent of traders surveyed used cell phones for their commercial operations.

phones might affect price dispersion, I construct a sequential search model in which traders search for the optimal sales price, net transport costs. The model is novel in two ways. First, it focuses on search from the supplier's perspective, which has not been widely addressed in the search literature. Second, the model allows traders to search for the optimal price of grain net transport costs, whereas most consumer search models assume that there are no additional costs involved once the price quote is obtained. The model predicts that equilibrium price dispersion will decrease in response to a reduction in search costs.

To empirically test the predictions of the model, I exploit the quasi-experimental nature of cell phone rollout to identify the impact of information technology on grain market performance in Niger, and in particular price dispersion. This involves estimating a difference-in-differences (DD) model with pooled treatments. My approach differs from the existing empirical literature on search technology and market performance in several ways. First, the quasi-experimental nature of cell phone rollout provides an opportunity to partially distinguish the impact of cell phone coverage from potentially confounding omitted variables. Second, as identifying the causal effects of cell phone coverage is subject to selection bias, I control for selection on observables by combining DD estimation with matching techniques. Finally, recognizing that the treatment effect might not be homogeneous, I allow for treatment effect heterogeneity over space and time.

For the empirical application, I construct two primary datasets. The first contains data on prices, transaction costs, agricultural production and rainfall obtained from Niger's *Système d'Informations sur le Marché Agricole* (SIMA) and other secondary sources. The dataset includes monthly grain price data over a seven-year period (1996-2006) across 42 domestic and cross-border markets in Niger. The second dataset is a unique and detailed panel survey of traders, farmers, transporters and market resource persons collected by the author between 2005-2007, comprising 395 traders and 205 farmers across 35 markets. This includes information on commercial operations and cell phone usage. In addition, the author collected information on the rollout of cell phone coverage between 2001-2006. The advantages of this dataset are twofold: first, it is a panel of individuals; and second, it provides information on traders' behavior and market characteristics that complement the time series data, thereby allowing us to explore the mechanisms behind the estimated treatment effect of cell phones on market performance.

The results indicate that the introduction of cell phone coverage reduces grain price dispersion across markets and the mean intra-annual coefficient of variation (CV). Cell phones have a greater impact on price dispersion where travel costs are higher, namely for markets that are more remote and those connected by unpaved roads. The effect is heterogeneous across time as well: cell phones have a larger impact upon price dispersion once a higher percentage of markets have cell phone coverage. Nevertheless, the evidence suggests that there are diminishing marginal returns to cell phones on price dispersion. These results are robust to controlling for selection on observables.

A central concern with the estimates is the possibility of alternative explanations for the empirical results. In the second part of the analysis, I test for alternative explanations and provide empirical evidence in support of specific mechanisms that could explain the impact of cell phones on market performance. To explore the sensitivity of the treatment effect to potential unobserved sources of bias, I conduct a series of robustness checks, which suggest that such bias is not a primary concern. As cell phone treatment potentially violates the stable unit treatment value assumption (SUTVA), I verify that the results are not solely driven by general equilibrium effects. Finally, recognizing that reductions in price dispersion could be due to growing collusive behavior, I calculate an index of market concentration. The results suggest that grain traders do not collude.

After testing for alternative hypotheses at the market level, this paper investigates the ways in which traders' behavior changes in response to the introduction of cell phones. I find that grain traders operating in markets with cell phone coverage search over a greater number of markets, have more contacts and sell in more markets. This provides evidence that the primary mechanism by which cell phones affect market performance is a reduction in search costs.

The reduction in price dispersion suggests that cell phones could lead to net welfare improvements. Cell phones are associated with a 3.5 percent reduction in consumer grain prices between 2001-2006, and a 4 percent reduction in prices during the 2005 food crisis. The lower relative prices in cell phone markets could have allowed individuals to consume millet for an additional 8-12 days. Cell phone towers are associated with an increase in trader welfare as well, with traders in cell phone markets receiving higher sales prices and annual profits. These findings therefore suggest that access to information technology can lead to welfare gains, although how these gains are shared among traders, consumers and farmers remains ambiguous.

This paper is broadly related to a body of research in economics on the relationship between costly search and market performance.[4] In particular, this paper shares with a smaller set of other papers a concern with assessing the impact of a reduction in search costs on price dispersion across markets. These papers examine the impact of information technology in the developed country context (Brown and Goolsbee 2002) or on a specific perishable commodity (Jensen 2007), and therefore raise concerns about generalizability. In comparison with this research, this paper examines a category of commodity (grains) that is highly relevant to the lives of rural populations in developing countries. It is important to establish (as this paper does), across a large number of cohorts and in a geographically dispersed sample.

Several other additional features help to distinguish this paper from existing research. First, this paper develops a novel theoretical model of trader (supplier) search, which reflects the realities of trade in many developing countries. Second, this paper goes beyond an estimate of the impact of information technology at the market-level to provide empirical evidence of the underlying causal

[4] Baye, Morgan and Scholten (2007) provide a survey of the theoretical and empirical literature on costly search and market performance.

mechanisms. Consistent with the predictions of the theoretical model, I find that cell phones result in a reduction in search costs, thereby allowing grain traders to search in more markets, to sell in more markets and to contact more individuals for market information. By contrast, existing papers in the developed and developing country context focus primarily on the impact of information technology on price dispersion.

The remainder of this paper proceeds as follows. Section 2 provides an overview of the grain market in Niger and the introduction of cell phones into the economy. Section 3 outlines a theoretical model of trader search, generating partial and general equilibrium predictions for the effect of mobile phones on traders' behavior and grain market performance. Section 4 discusses the data and empirical strategy. Section 5 presents the main empirical results, while Section 6 conducts a variety of robustness checks. Section 7 explores the mechanisms behind the treatment effects, and Section 8 assesses the impact of cell phones on consumer and trader welfare. Section 9 concludes.

2. Background on Niger

2.1. The Grain Market in Niger

With a per capita GNP of US$230 and an estimated 85 percent of the population living on less than US$2 per day, Niger is ranked 174th (out of 177) on the United Nations' Human Development Index (UNDP 2008). Agriculture employs more than 80 percent of the total population and contributes approximately 40 percent to Gross Domestic Product (GDP). The majority of the population consists of rural subsistence farmers, who depend upon rainfed agriculture as their main source of food and income. The main grains cultivated are millet, sorghum, rice, fonio and maize, with cash crops including cowpea, peanuts, cotton and sesame.

A variety of market actors are involved in moving grains from the farm to consumers in Niger. Primary actors include farmers, who produce, sell and buy millet, sorghum and cowpea; traders, including retailers, intermediaries, semi-wholesalers and wholesalers; transporters; and rural and urban consumers.[5] Grains are produced by farmers, who sell their production directly to intermediaries. Intermediaries sell directly to wholesalers in local markets. Wholesalers are primarily responsible for inter-regional trade, selling the commodity to other wholesalers, retailers or consumers. Retailers sell directly to both urban and rural consumers. As there is only one growing season per year (October), traders begin importing grains from neighboring countries (Benin, Burkina Faso, Mali and Nigeria) in April, once the local supply is depleted.

Traders buy and sell grains through a system of traditional markets, each of which is held on a weekly basis. The density of grain markets varies considerably by geographic region, with inter-market distances ranging from 10 km to over 900km.[6] The number of traders per market ranges from 24 to 353, with retailers accounting for over 50 percent of all traders. While a market information system has existed in Niger since 1980s, 89 percent of grain traders surveyed by the author stated that they obtain price information through their own personal and professional networks. Previous analyses suggest that grain markets in Niger are somewhat integrated, but that there is substantial inter- and intra-annual variation (Aker, 2008). The average correlation coefficient for prices among grain markets is .55, well below price correlation coefficients computed for other agricultural products in the developing world (Timmer 1974, Trotter 1991).

2.2. Cell Phones

Cell phone service first became available in part of Niger in October 2001. Although private cell phone companies initially intended to provide universal coverage, due to high fixed costs and uncertainty about potential customers, cell phone service was introduced gradually. The initial criteria for introducing cell phone coverage to a location were twofold: first, whether the town was

[5] Intermediaries are responsible for purchasing grains directly from farmers and selling it to wholesalers or retailers. Wholesalers and semi-wholesalers have greater financial resources, with total sales between 1-3 metric tons (MT) (semi-wholesalers) or greater than 3 MT (wholesalers). Retailers are small-scale traders who sell only in small quantities, usually less than one bag.
[6] This refers to the distance between markets for which trade occurred between 2000-2006.

an urban center; and second, whether the town was located near an international border.[7] During the first three years of cell phone expansion, the average distance between markets with cell phone coverage was 367km, ranging from 35km to 900km.

Although landlines existed prior to 2001, Niger has the second lowest landline coverage in the world, with only 2 landlines available per 1000 people, as compared to 113 landlines per 1000 in South Africa (World Bank 2005).[8] Figure 1 shows the spatial rollout of cell phone coverage by market and by year. Figure 2 shows the number of cell phone subscribers relative to the total number of landlines. Cell phone coverage and subscribers increased substantially between 2001 and 2006, with 76 percent of grain markets having coverage by 2006. By contrast, the number of landlines remained relatively stable during this period, and landlines were primarily available in large urban centers.[9]

Despite the increase in cell phone coverage since 2001, Niger still has the lowest adoption rate in Africa. There were an estimated 397,000 cell phone customers in 2006, representing 4 percent of the population (MTC 2006). Nevertheless, cell phones spread quickly among urban residents, functionaries and traders. As of 2006, 29 percent of grain traders surveyed owned a cell phone for their trading operations, ranging from 18 to 40 percent in specific markets. Cell phones were initially adopted by wholesalers, who were more likely to engage in inter-regional trade. Wholesalers were also more likely to be able to afford the phones, which initially cost US$30.

3. A Model of Information, Search and Price Dispersion

How has the introduction of a new search technology – namely, cell phones – affected traders' behavior and grain market performance in Niger? Since the 1960s, a large literature on

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[7]Based upon the author's personal interviews of cell phone companies in Niger. Cell phone companies prioritized towns along the borders with Benin, Burkina Faso, Mali and Nigeria.

[8]Only the Democratic Republic of Congo has fewer landlines per capita in sub-Saharan Africa, with .8 landline per 1000 people.

[9] There were an estimated 600 telecenters in Niger as of 2006, primarily in large urban centers. Of these, only 19 were classified as "multifunctional", i.e., offering landline and cell phone services. World Bank (2005).

consumer search theory has emerged, in an effort to explain how changes in search costs affect market actors' behavior and equilibrium price dispersion. The consumer search literature is dominated by two approaches. The "search-theoretic" approach assumes that it is costly for consumers to collect information about prices (Stigler 1961, Reinganum 1979, MacMinn 1980, Stahl 1989, Janssen and Moraga-González 2004). A second approach minimizes the role of marginal search costs, assuming that a subset of consumers can access price information by consulting an "information clearinghouse" (Salop and Stiglitz 1977, Varian 1980, Spulber 1995, Baye and Morgan 2001).

While most search-theoretic models have been used to explain the existence of price dispersion for homogeneous goods, the comparative static predictions of these models can be ambiguous. The sequential search models of Reinganum (1979) and Stahl (1989) predict that a reduction in search costs will decrease the variance of equilibrium prices, while MacMinn (1980) shows that a reduction in search costs can increase price dispersion. These contrasting theoretical predictions are due to different assumptions with respect to consumers' demand functions, the fixed or sequential nature of search and firm cost heterogeneity (Baye, Morgan and Scholten 2007).[10]

This paper builds upon the sequential search-theoretic models of Reinganum (1979) and Stahl (1989) to develop a model of trader sequential search. The model presented here is novel for two reasons. First, it focuses on search from the trader's (supplier's) perspective, which has not been widely addressed in the search literature.[11] Second, while most consumer search models identify an expected benefit function, they often assume that there are no additional costs involved to purchasing the good once the minimum price quote is obtained. The model presented in this

[10]Reinganum (1979) develops a model of sequential search and firm cost heterogeneity, whereas MacMinn (1980) develops a model of fixed sample search and firm cost heterogeneity.

[11]In his work on the impact of cell phones on the fisheries sector in India, Jensen (2007) proposes a two-market model of fishermen arbitrage in order to derive the decision rule for a fishermen's search technology and its impact on inter-market price dispersion.

paper relaxes this assumption by allowing expected benefits to be a function of the price net transport costs, thereby bringing theory closer to the realities of grain trade in sub-Saharan Africa.

Assume that there is a homogeneous good, millet, and a finite number of traders with strictly increasing concave utility functions over income.[12] Traders know the distribution of prices across all markets at time t, but not the exact market for each price. Each trader is based in a home market j, and must pay a constant per-km known cost of transporting millet to the final sales market. Traders engage in sequential search for their optimum price net transport cost, but must pay a constant per-search cost, c.[13]

Millet prices across markets have a probability density function (pdf) $f(p)$ and a cumulative density function (cdf) $F(p)$ on the support $[\underline{p}, \overline{p}]$. Each trader with home market $j, j = 1,....,J$, faces a distribution of prices net transport costs, $F_j(p)$, on the support $[\underline{p}_j, \overline{p}_j]$. A key assumption is that $F_j(p)$ is unique to the trader, and that he repeatedly samples from this distribution.[14]

Suppose that the trader has already searched an arbitrary number of markets, n, and that the optimal (ie, highest) price net transport costs is z. The trader searches an additional time and realizes a price net transport cost of p_{n+1}. The trader "wins" from this action if the realized price less transport costs is greater than z and "loses" otherwise.

12Although traders could simultaneously be buyers and sellers of millet, I assume that traders buy in their home market and do not search for the best purchase price.

13 The assumption of a constant per-search cost coincides with the consumer search literature and once cell phones are introduced. However, the model can be generalized to include a constant per-km search cost, whereby the total cost of search is increasing in distance, k, s.t. $c_{ij} = c * k_{ij}$.

14 This implies that a trader with home market *j* samples from one distribution of prices net transport costs. If that trader travels to market *i*, he does not face a new distribution. I assume throughout that $F(p)$ and $F_j(p)$ are nondegenerate distributions.

If the trader "wins", his benefit is $U_{win}^{gain} = u(p_{n+1}) - u(z)$. If the trader "loses" his gain in utility is zero, as he or she can simply sell at the price (net transport cost) z in the previous market. Consequently, the traders' marginal expected benefit function for the $n+1^{th}$ search is:

$$\begin{aligned} B_j(z) &= \int_z^{\bar{p}_j} \left[u(p) - u(z)\right] f_j(p)\,dp + \int_0^z \left[u(z) - u(z)\right] f_j(p)\,dp \\ &= \int_z^{\bar{p}_j} \left[u(p) - u(z)\right] f_j(p)\,dp \end{aligned} \tag{1}$$

where $(z, \bar{p}_j]$ is the range of price (net transport cost) realizations where the trader wins. One finds that $B_j(z) > 0$ and $B_j'(z) \le 0$, so that the expected benefit function is positive but decreasing.[15]

The trader will weigh his expected marginal benefit with the marginal cost of additional search, defined as his marginal net gain function: $h_j(z) \equiv B_j(z) - c$.[16] The net gain function defines a decision rule for search: If $h_j(z) \le 0$, the trader will not engage in an additional search; if $h_j(z) > 0$, the trader will search until he finds a price net transport cost quotation that is at or above his reservation price, r_j, which solves:

$$h_j(r) = B_j(r) - c = 0 \tag{2}$$

Equation (2) can be used to derive partial equilibrium comparative statics for the trader's behavior. Taking the total derivative with respect to r_j and c yields:

$$\frac{dr_j}{dc} = \frac{1}{u'(r_j)\left[F_j(r_j) - 1\right]} < 0 \tag{3}$$

for all traders with home market j. Equation (3) implies that a decrease in search costs will increase the trader's reservation price.

15 The proof is provided in Appendix 1.
16This formulation of the marginal benefit function coincides with the consumer search literature (Baye, Morgan and Scholten 2007). Tthe search cost could also be included as an element of the marginal benefit function.

Although the choice variable in this model is the reservation price (net transport costs), it is instructive to derive the trader's expected number of search markets. Assuming that the trader never searches the same market twice, an expression for the expected number of searches can be derived. For traders with home market *j* and reservation price r_j, define $m_j \in \{1,...,J\}$ to be the number of markets with price net transport costs higher than r_j. Let the discrete random variable $N \in \{1,....,J-m_j+1\}$ define the number of searches.[17] This implies that:[18]

$$E(N)=\sum_{n=1}^{J-m_j+1} n\Pr[N=n]=\frac{J+1}{m_j+1} \tag{4}$$

and $\frac{dE(N)}{dm_j}<0$. Combining this with the comparative static $\frac{dr_j}{dc}<0$, and assuming that $\frac{dm_j}{dr_j}\le 0$ (a higher reservation price will result in a fewer number of successes), then:

$$\frac{dE(N)}{dc}=\frac{dE(N)}{dm_j}*\frac{dm_j}{dr_j}*\frac{dr_j}{dc}\le 0 \tag{5}$$

In other words, the number of markets over which traders search will increase as search costs fall.

In addition to these partial equilibrium results, I am interested in general equilibrium predictions. In order to derive them, I assume that there are homogeneous consumers with identical demand for millet. If optimizing consumers ignore traders' reservation prices, then they will assume a distribution of prices on the support $[\underline{p},\overline{p}]$. As traders are unwilling to supply millet at prices that are below their reservation price, this would imply a distribution of prices:

$$F(p)=\hat{F}(p) \text{ if } p>r_{\min}\text{, and 0 if } p\le r_{\min} \tag{6}$$

[17]The upper bound on this expression is $J-m_j+1$. Since there are only $J-m_j$ possible failures, the maximum number of searches is trader is $J-m_j+1$.

[18] The expression for the pdf of N is provided in Appendix 1. Using an inductive proof shows that these probabilities sum to one and that this expression constitutes a well-defined pdf for the number of searches until the first success.

where $r_{\min}$ is the minimum reservation price across all traders.[19]

In equilibrium, the variance in posted prices is given by:

$$\sigma^2 = E[p^2] - (E[p])^2 = \int_{r_{\min}}^{\bar{p}} p^2 dF(p) - \left(\int_{r_{\min}}^{\bar{p}} p dF(p) \right)^2$$

$$= \int_{r_{\min}}^{\bar{p}} p^2 \hat{f}(p) dp + \hat{F}(r_{\min}) r_{\min}{}^2 - \left(\int_{r_{\min}}^{\bar{p}} p \hat{f}(p) + \hat{F}(r_{\min}) r_{\min} \right)^2 \qquad (7)$$

where $\hat{f}(p)$ is the pdf of $\hat{F}(p)$ (Reinganum 1979, Baye, Morgan and Scholten 2007). Taking the derivative of Equation (7) with respect to $r_{\min}$, it can be shown that $\frac{d\sigma^2}{dr} \leq 0$. Since $\frac{dr}{dc} \leq 0$, then $\frac{d\sigma^2}{dc} \geq 0$, implying that a reduction in search costs should decrease the variance of prices.

Linking the model to the data is straightforward. The introduction of cell phones in Niger decreases traders' per-search cost as compared to personal travel. Although cell phones require an initial fixed cost, the variable costs associated with cell phone use are significantly lower than equivalent travel and opportunity costs.[20] Cell phones not only decreased traders' travel costs, but also the opportunity cost of traders' time; an average trip to a market located 65 km away can take 2-4 hours roundtrip, as compared to a two-minute call. Using a local daily wage of 500 CFA (US$1) per agricultural laborer in Niger, the total costs of obtaining information from a market 65km away might have fallen by 50 percent between 2001-2006.[21]

The theoretical model can be used to derive the following comparative statics:

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[19] This assumes that there is a single truncation of the distribution from below, with the truncation occurring at the minimum reservation price across all traders. To establish that this is an equilibrium distribution of prices, traders facing this new distribution must not have an incentive to change their reservation price.

[20] In 2006, a two-minute call to a market located 65 km away cost US$1, as compared US$2 for roundtrip travel. Cell phone usage rates were 160-195 CFA/minute ($ .35-.43/minute) and 35 CFA per text message ($ .07/minute).

[21] Estimated search costs pre-cell phones were US$2.50, with US$2 for travel and US$.50 for opportunity costs. Estimated search costs post-cell phones are US$1.

- The introduction of cell phones will lead to an *increase* in traders' reservation prices, r_j, as compared to the traditional search technology, $\frac{dr_j}{dc} < 0$
- The introduction of cell phones will lead to an *increase* in the number of markets over which traders search, $\frac{dE(N)}{dc} < 0$
- The introduction of cell phones will reduce price dispersion among markets with cell phone coverage, $\frac{d\sigma^2}{dc} > 0$

The second and third hypotheses are tested empirically in the following sections.

4. Data and Measurement

This paper uses two primary datasets. The first is a rich dataset of prices, transaction costs, agricultural production and rainfall, obtained from secondary sources in Niger. This dataset includes monthly cereal (millet and sorghum) data over a ten-year period (1996-2006) across 42 domestic and cross-border markets in Niger. In addition, time-series data on gas prices, cell phone coverage, road quality, trade flows and district population levels were also collected.

The second dataset is a unique panel survey of traders, farmers, transporters and market resource persons collected in Niger by the author between 2005-2007. The survey interviewed 395 traders located in 35 markets across six geographic regions of Niger. Prior to the first round of data collection, the author developed a census of all grain markets, and markets were randomly sampled based upon the criteria of geographic location, market size and their 2005 food crisis status. Within each market, I conducted a census of all grain traders operating on the market, noting the type of trader (retailer, intermediary, semi-wholesaler or wholesaler) and gender. Using these census data, the author selected a stratified random sample of traders. A team of trained local enumerators interviewed traders and farmers on the day of the market. Over 98.5 percent of traders interviewed during the first phase also participated in the second phase (with attrition primarily due to illness, death or travel to Mecca for the *Hadj*). Consequently, attrition is not a major concern.

The traders and market resource persons who participated in the survey provided detailed information about their demographic background and commercial operations during the 2005/2006 and 2006/2007 cereal marketing seasons. Enumerators also asked a subset of questions about the 2004/2005 marketing season.

Key trader and market-level variables from the panel data survey are described in Table 1. Two aspects of the trader survey data are noteworthy. First, grain traders in Niger trade primarily in agricultural outputs, have limited commercial assets and store for less than one month. Second, traders' commercial operations are self-reported and retrospective for 2004/2005.

5. Empirical Strategy

In order to assess the impact of the staggered introduction of cell phone coverage on traders' behavior and grain market performance in Niger, this paper employs a two-part empirical strategy. During the first part of the analysis, I use the time series panel data to estimate the impact of cell phones on price dispersion across grain markets between 1999-2006. In this case, treatment is defined as the presence of a cell phone tower in a particular market, not cell phone adoption. In the second part of the analysis, I use trader-level survey data to investigate alternative explanations and estimate how traders' behavior changes in response to cell phone coverage.

5.1. Impact of Cell Phones on Market Performance

The theoretical model of trader search posits that equilibrium price dispersion will decrease as search costs are reduced. The search literature primarily uses three measures of price dispersion: the sample variance of prices across markets over time (Pratt, Wise and Zeckauser 1979), the CV across markets over time (Eckard 2004, Jensen 2007), and the maximum and minimum (max-min) prices across markets (Pratt, Wise and Zeckhauser 1979, Jensen 2007). In his analysis of the impact of cell phones on the fisheries sector in Kerala, India, Jensen (2007) uses the max-min and CV as measures of price dispersion. As cell phone coverage in Kerala was phased in by geographic region, markets were in close geographic proximity, and so these measures were appropriate for the local context. By contrast, cell phone coverage in Niger was phased in according to urban status, and initial distances between cell phone markets ranged from 38-900 km. Consequently, the traditional measures of price dispersion are not appropriate for this quasi-experimental setup. The primary measure of market performance is the price difference between markets *i* and *j* at time *t*, defined as $Y_{ij,t} = | p_{it} - p_{jt} |$. The CV is also used as a robustness check.

To exploit the spatial and temporal variation in the rollout of cell phone towers, I augment the standard difference-in-differences (DD) framework by estimating a double DD specification (Meyer 1995, Bertrand, Duflo and Mullainathan 2004).[22] Letting $Y_{ij,t}$ represent the value of the outcome in market pair *ij* at time *t,* I examine the change in $Y_{ij,t}$ before and after the introduction of cell phone towers in each market pair. I first estimate the following DD equation:

$$Y_{ij,t} = \beta_1 + \beta_2 cell_{ij,t} + \gamma Z_{ij,t} + a_{ij} + \theta_t + u_{ij,t} \tag{8}$$

where $Y_{ij,t}$ is the absolute value of the price difference of millet between market *i* and market *j* at time *t*; $cell_{ij,t}$ is a variable that is equal to one in all periods *t* in which both markets *i* and *j* have mobile phone access, and 0 otherwise.[23] $Z_{ij,t}$ is a vector of exogenous regressors that affect price dispersion, such as transport costs, the presence of drought, road quality and the number of traders operating in a market, some of which vary over time. θ_t is time fixed effects, either monthly or yearly, and a_{ij} captures unobservable market-pair specific effects. I allow the unobserved fixed effects to be correlated with $Z_{ij,t}$ and $cell_{ij,t}$. $u_{ij,t}$ is an error term with zero conditional mean, such

[22] The control structure is twofold: temporal, as treated years (2001-2006) are compared with untreated years (1999-2001); and cross-sectional, as treated market pairs are compared with untreated market pairs at time *t*.
[23] The DD estimation should include a variable (*evercell$_{ij}$*) that is equal to 1 if both markets ever received treatment (a cell phone tower) between 2001-2006, 0 otherwise. This variable will only be identified if fixed effects are not included in the model, or if fixed effects are interacted with time. Consequently, this variable does not appear in our specification.

that $E[u_{ij,t} \mid cell_{ij,t}, Z_{ij,t}, a_{ij}, \theta_t] = 0$; this assumes that the error terms are uncorrelated with the exogenous regressors in each period after controlling for unobserved time-invariant heterogeneity. The parameter of greatest interest is β_2. The key identifying assumption is that differential trends in outcomes are the same across treated and untreated market pairs.

Equation (8) can either be estimated via fixed effects transformation or first differencing.[24] As the data are positively serially correlated in levels, I transform equation (8) via first differences to remove the unobserved heterogeneity.[25] This yields the main estimating equation:

$$\Delta Y_{ij,t} = \beta_2 \Delta cell_{ij,t} + \gamma \Delta Z_{ij,t} + \Delta \theta_t + \Delta u_{ij,t} \tag{9}$$

where β_2 remains the primary parameter of interest, measuring the average change in $Y_{ij,t}$ over each time period for the treated and untreated market pairs. For the OLS estimate of β_2 to be consistent, $\Delta u_{ij,t}$ must be uncorrelated with the first-differenced regressors.

I modify equation (9) in a variety of ways. To assess the heterogeneous impact of cell phones across space, I interact cell phones with gas prices, distance and road quality. Assuming that market performance in period t might depend upon performance in period $t-1$, I include a lagged dependent variable. These modifications will be discussed in Section 6.

To assess heterogeneous impacts over time, I modify equation (9) to include a market pair-specific time trend, a variable measuring the percentage of markets with cell phone access at time t and a series of dummy variables pre- and post-treatment. I then exploit the variation in the timing of introduction of cell phones across market pairs by estimating year-specific regressions. Using the

[24] While both will be unbiased and efficient under standard assumptions, first differencing will be more efficient than fixed effects in the presence of a serial correlation problem (Wooldridge 2002).

[25] First differencing does not completely eliminate the serial correlation problem, but minimizes the impact. I therefore correct for serial correlation in the standard error estimation. Stationarity tests show that price differences are integrated of degree one, so first differences will be integrated of degree zero.

DD framework for each year, I examine the change in outcomes by treatment group between the pre-treatment period and year y:

$$Y_{ijt,y} = \alpha + \beta_1 cell_{ij,y} + \beta_2 cell_{ij,y} * year_y + \beta_3 year_y + u_{ij,y} \quad (10)$$

[26]

where $Y_{ijt,y}$ is the absolute value of the average price difference between markets *i* and *j* at time *t* (months) during year y; $cell_{ij,y}$ is an indicator variable equal to 1 if the market pair was treated in year y, 0 otherwise; $year_y$ is the year of cell phone coverage $(y = 0,1,2,3,4,5)$ where $y = 0$ denotes 1999-2001; $cell_{ij,y} * year_y$ is the interaction between the treatment group and the year of treatment; and $u_{ij,y}$ is an error term with 0 conditional mean. The key parameter of interest is β_2. Additional exogenous regressors that affect treatment are also included in some specifications.

5.2. Dealing with Endogenous Placement of Cell Phone Towers

The fundamental empirical problem in estimating the impact of cell phone coverage is that the outcomes for a treated pair in the absence of treatment cannot be observed – in this instance, cell phone coverage. The standard solution to this problem is to identify a relevant control group and estimate the average treatment effect (ATE) by taking the difference in outcomes for the treated and control groups (Rubin 1974, Imbens 2004). The estimated ATE will be unbiased when treatment assignment and the potential outcomes are independent, which is assured with random assignment.

As initial cell phone coverage was not randomly assigned, but based upon a town's urbanization status and proximity to a border, there could be multiple types of omitted variable bias. I am primarily concerned with selection bias, whereby current market outcomes are the result of pre-treatment time-invariant or time-variant characteristics that led to the placement of cell phone

[26] A key element for estimating equation (10) is the definition of the treated and untreated market pairs. While treatment status can be defined in a variety of ways, the estimation strategy focuses on two primary categorizations: 1) comparing treated and untreated groups within each year *y*; and 2) comparing treated groups in year *y* with a constant control group.

towers. To deal with this concern, I attempt to identify cases where treatment is conditionally independent; in other words, cell phone coverage is independent of the potential outcomes, conditional on a set of observed pre-treatment variables (Rubin 1978, Rosenbaum and Rubin 1983, Imbens 2003).

Table 2 shows the unconditional differences in means and distributions for pre-treatment outcomes and covariates. Panel A shows the differences in means for treated and untreated market pairs, whereas Panel B shows the difference in means for treated and untreated markets.[27] The difference in average price dispersion in the pre-treatment period (1999-2001) was small and not statistically different from zero. Most of the unconditional differences in means for the pre-treatment covariates are not statistically significant, with the exception of whether the market was located in an urban center and road quality.[28] The magnitude of the difference in road quality between treated and untreated markets is small, and only significant at the 10 percent level.

A more robust analysis of the potential overlap problem is a comparison of the difference in means with the standard deviation.[29] Comparing the difference in average means with the standard deviations, the dataset is well-balanced; the difference in means between treatment and control groups is never more than 0.21 standard deviations for any covariate.[30] The only exception to this case is the difference in means for urban centers.

Based upon these tests, cell phone and non-cell phone markets appear to differ only according to their location in an urban center and road quality in the pre-treatment period.[31] The relationship between an urban center and cell phone coverage is expected, as a market's probability

[27] Treated market pairs are those cases where both markets received cell phone coverage between 2001-2006. Untreated market pairs are those pairs where at least one market never received cell phone coverage. Treated markets are those markets that received cell phone coverage between 2001-2006, and untreated markets are those that never received cell phone coverage.

[28] Border markets are included in the analysis but are not included as a separate category, as they are a subset of urban centers.

[29] As the t-statistic is equal to the normalized difference multiplied by the square root of the sample size, a larger t-statistic could simply indicate a larger sample size (Imbens and Wooldridge 2007).

[30] A difference in average means larger than 0.25 standard deviations is considered to be substantial (Imbens and Wooldridge 2007). For road quality, the difference in means is .1, and the s.d. is .465. The difference therefore represents .21 of the s.d. for road quality.

[31] Using the Kolmogorov-Smirnov test, the differences in distributions for urban center, price dispersion and transport costs are statistically significant. However, a graphical analysis shows that treated and untreated pairs have similar distributional patterns.

of receiving cell phone coverage, at least initially, depended upon whether it was located in an urban center.

As cell phone coverage was phased in over time, it is also important to test for differences in pre-treatment trends in market outcomes. If trends across treated and untreated groups were the same during the pre-treatment period, they are more likely to have been the same in the post-treatment period. The equation used to test for the equality in pre-treatment trends is:

$$Y_{ij,t} = \beta_0 + \beta_j pre_j + \sum_{y=1}^{5} \theta_{jy} pre_j * cell_y + u_{ij,t} \quad (11)$$

where $Y_{ij,t}$ is price dispersion between markets *i* and *j* at time *t*; pre is a variable for the change in the pre-treatment periods (1999-2001); and $cell_y$ is equal to 1 if the market pair has cell phone coverage during year *y*, and 0 otherwise. If the θ_{jy} 's are not statistically different from zero, then the pre-treatment trends do not statistically differ among market pairs that received cell phone coverage in different years. The results suggest that pre-treatment trends across market pairs are not statistically different from zero, with the exception of the market pair that received coverage in 2001.[32]

5.3. Estimation under Selection on Observables

To control for potential selection bias, I combine the estimation strategy outlined in equations (8)-(10) with techniques that match treated and untreated market pairs. Results can be sensitive to the estimator chosen, so I use two alternative methods to construct an appropriate counterfactual. In the first method, I include a parametric estimation of the propensity score as an additional control in the DD equations. Under the conditional independence assumption, consistent ordinary least squares (OLS) estimates of the treatment effect can be calculated. A more efficient and consistent approach, however, is a weighted least squares (WLS) regression (Hirano and Imbens

[32] Results are provided in Appendix 2. The 2001 observation is later dropped from the estimations as a robustness check.

2002).[33] This estimator will be "doubly robust" as long as the regression model and the propensity score are specified correctly (Robins and Ritov 1997, Hirano and Imbens 2002).[34]

6. The Impact of Cell Phones on Market Performance

6.1. Average Treatment Effects

Before turning to the regression specification with separate treatment effects, I first pool the treatments and estimate equation (9). Table 3 presents the regression results of the DD model using a first-differenced transformation, controlling for exogenous regressors, market-pair fixed effects and time fixed effects.[35] Column 1 shows that cell phones are associated with a negative (-4.7 CFA/kg) and statistically significant reduction in price dispersion across markets, indicating that price dispersion between markets with cell phone coverage is 21 percent lower than those without cell phone coverage.[36] Transport costs are associated with higher price dispersion between markets and are statistically significant at the 1 percent level. The presence of drought in one market is associated with a statistically significant increase in price dispersion across markets.[37] Column 2 uses an alternative measure of market performance, the intra-annual CV for market *i*. Cell phone towers are associated with a .04 and statistically significant reduction in the CV, implying that the intra-annual price dispersion is 12 percent lower in markets with cell phone coverage. This suggests that consumers located in cell phone areas are subject to relatively lower intra-annual price risk.

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33 For the WLS representation, I weight the observations by a parametric estimate of the propensity score, where the weights are the following: $\lambda_{ij} = \sqrt{\frac{cell_{ij,t}}{\hat{p}(X_{ij,0})} + \frac{1-cell_{ij,t}}{1-\hat{p}(X_{ij,0})}}$.

34 This approach is an efficient estimator of the ATE if there are homogeneous treatment effects, and an efficient estimator of the average treatment effect on the treated (ATT) if there are heterogeneous treatment effects. Although the weighted propensity score is more efficient, it is also sensitive to a misspecification, which can result in additional bias.

35 For all specifications, the Law of One Price (price differences net transport costs) was also used as an alternative dependent variable. The coefficients were nearly identical, and so these results are not reported.

36 The percentage change is calculated as the treatment effect relative to the mean price dispersion for non-cell phone markets in the pre-treatment period.

37 Drought in a market is defined as two standard deviations below the average rainfall during the rainy season, and/or the lack of rainfall for more than 15 consecutive days. Separate variables for drought in both markets and drought in one market were included in certain specifications as a robustness check, which did not affect the magnitude nor statistical significance of the cell phone variable.

The results are robust to the inclusion of a market pair-specific time trend to control for an additional source of heterogeneity (Columns 3-4). Including the trend increases the point estimates slightly, but does not affect the standard errors. The specification in Column 5 controls for monthly fixed effects, as opposed to yearly fixed effects, as well as the market pair-specific time trends. The coefficient estimate for cell phone decreases, from 4.7 to 4.4, yet remains statistically significant.[38] This is not surprising, as the treatment assignment is monthly, and monthly fixed effects account for a large degree of temporal variation. In addition, using first differences significantly reduces the cross-sectional variation in cell phone treatment, thereby increasing the standard errors. Using the conservative estimate of -4.4 CFA/kg, cell phone coverage is associated with a 20 percent reduction in price dispersion as compared to untreated market pairs.[39]

Until now, a key assumption of the identification strategy has been that the $\Delta u_{ij,t}$ are uncorrelated with the first-differenced regressors. This assumption rules out cases where future explanatory variables react to changes in the idiosyncratic errors. Nevertheless, it is reasonable to assume that grain market performance depends upon market performance in a previous period. I therefore modify equation (9) to include a lagged dependent variable:

$$\Delta Y_{ij,t} = \rho \Delta Y_{ij,t-1} + \beta_2 \Delta cell_{ij,t} + \gamma \Delta Z_{ij,t} + \Delta \theta_t + \Delta u_{ij,t} \qquad (12)$$

where ρ can be interpreted as the market adjustment speed. As the inclusion of a lagged dependent variable with fixed effects induces an endogeneity problem, I control for endogeneity by using the Arellano-Bond Generalized Method of Moments (GMM) estimator (Arellano and Bond 1991).[40]

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[38]If 84 monthly time dummies are included, the magnitude of the cell phone variable drops to -1.64 and becomes statistically significant at the 10 percent level. Using this conservative estimate, cell phones are still associated with a 6.4 percent reduction in price dispersion.

[39]In order to show how the effect varies with the intensity of treatment, I also redefine the treatment variable into three binary variables: a variable that is equal to 1 when both markets have treatment, a variable that is equal to 1 when one market has treatment, and a variable equal to 1 if neither market ever received treatment. For all specifications, the treatment effect is strongest when both markets are treated. There is no statistically significant effect when neither market is treated.

[40] After first-differencing, the lagged-dependent variable is correlated with the composite error term through the contemporaneous terms in period t-τ. Hence, instrumental variables are required. I therefore use the past values of the explanatory variables as instruments for the lagged dependent variable in a GMM framework (Arellano and Bond 1991). As the consistency of the estimator

Columns 6 and 7 present the results of the model with a lagged dependent variable, using the Arellano-Bond GMM estimator. Controlling for transport costs, drought, and time fixed effects, the coefficient on the lagged dependent variable is negative in both models, implying that it takes over 3 months for price differences across markets to adjust.[41] The coefficient on cell phones is still negative and statistically significant at the 5 percent level (Column 6), representing the initial impact of cell phone coverage. However, in the presence of a lagged dependent variable, the long-run treatment effect is measured as $\frac{\beta_2}{1-\rho}$. Using this formula, cell phones are associated with a 1.86 CFA/kg and statistically significant reduction in price dispersion in the long-term. This is robust to the inclusion of monthly fixed effects (Column 7), although the magnitude and statistical significance of the coefficient drops when 84 monthly time dummies are included. This is not surprising, as monthly time dummies account for most of the cross-sectional and temporal variation in treatment.

6.2. Heterogeneous Treatment Effects

Pooling the treatments measures the average impact of cell phones on price dispersion, thereby assuming a homogenous treatment effect. To identify treatment effect heterogeneity across space, I interact the cell phone treatment with petrol prices, distance and road quality. The regression results for these interactions are provided in Table 4. The coefficient on the interaction term between cell phones and petrol prices is not statistically significant (Column 1).[42] The joint effect of cell phones and petrol prices, evaluated at the mean petrol price, is -5.5 CFA/kg and strongly statistically significant, suggesting that cell phones are associated with a 25 percent

depends upon the validity of these instruments, a necessary condition is the lack of τ -order serial correlation in the error terms after first-differencing. I conduct the Sargan test of overidentifying restrictions and test for no serial correlation in the errors. The *z*-statistic of the Sargan test is -.19, so we cannot reject the null hypothesis of no autocorrelation of order 2 in the residuals.

[41] The coefficient on the lagged dependent variable can be interpreted as the speed of adjustment. I use the concept of a "half-life" to interpret the results, calculated as $\ln(.5) / \ln(1+\rho)$.

[42] As the Government of Niger fixes petrol prices across all markets on a monthly basis, there is only temporal variation in petrol prices.

reduction in price dispersion. Once monthly fixed effects and market-pair time trends are included (Column 2), the magnitude of the cell phone coefficient decreases to -4 CFA/kg. Overall, the joint effect of cell phone coverage is negative and statistically significant at the 1 percent level.

To determine how the impact of cell phone differs across space, I interact the cell phone variable with a distance variable, with *distance dummy*=1 if the distance between two markets is greater than 350 km, and 0 otherwise. The interaction term shows that there is a negative and statistically significant relationship between cell phones and distance, suggesting that cell phones have a stronger impact upon price dispersion for those markets that are farther apart (Columns 3-4). The joint effect suggests that cell phones are associated with a 7 CFA/kg reduction in price dispersion for markets separated by a distance greater than 350 km.

To further disentangle the nonlinear relationship between cell phones and distance, I split the sample into short haul (<100km), medium haul (100-550 km) and long haul (>550 km) market pairs (Columns 5, 6 and 7). Cell phones have a negative effect on price dispersion for short- and medium-haul markets, although this effect is strongest and statistically significant for medium-haul markets (Column 6). This suggests that cell phones are more useful when markets are farther apart, but that there is a diminishing marginal effect of cell phones on price dispersion after a maximum distance.[43] The results are similar when interacting cell phones with road quality (Column 8). Cell phones have a stronger impact on price dispersion for markets linked by unpaved roads, and the joint effect is statistically significant at the 1 percent level.[44]

As cell phone towers were phased in between 2001-2006, it is reasonable to assume that cell phones became more useful to traders as a greater number of markets received cell phone

[43]Regressing price dispersion on cell phones and distance reveals that there is a quadratic relationship between distance and price dispersion. The maximum point of the function is at 589 km. This suggests that cell phones have a negative effect on price dispersion for markets less than 589 km apart, but a diminishing marginal effect for markets beyond this distance.
[44]Splitting the sample between paved and unpaved roads (Columns 9 and 10), cell phones are associated with a 7.3 CFA/kg reduction in price dispersion for markets with unpaved roads.

coverage.[45] To identify treatment effect heterogeneity over time, I interact the cell phone treatment variable with a variable that measures the percentage of markets that have cell phone coverage during a particular period (*network*$_t$). The regression results from these interactions are presented in Table 5. The interaction term between cell phones and network coverage is strongly negative (-11.8 CFA/kg) and statistically significant at the 1 percent level (Column 1), suggesting that the average effect of cell phones becomes stronger as more market pairs have cell phone coverage. When 14 percent of market pairs had cell phone coverage in 2003, price dispersion was 1.6 CFA/kg lower in cell phone markets. When over 76 percent of market pairs had cell phone coverage in 2006, price dispersion was 8 CFA/kg lower in cell phone markets.[46] This result is similar when using the CV (Column 2). Such findings are intuitive: cell phones are more likely to be useful as network coverage increases, since traders are able to search over a larger number of markets using the new technology.

The interaction term between cell phones and the network variable provides evidence of the heterogeneous impact of cell phones over time. Regressing price dispersion on a quadratic of network coverage suggests that there is a nonlinear relationship between the two. To investigate this nonlinear relationship, I introduce a series of dummy variables for the number of months before and after a market pair receives cell phone coverage (Jacobson, Lalonde and Sullivan 1993). Accordingly, $D_{ij,t}^{k}=1$ if, in period *t,* market pair *ij* received cell phone coverage *k* months earlier (or, if *k* is negative, market pair *ij* received cell phone coverage -*k* months later). By restricting attention to these dummy variables, I formalize the idea that a market pair that received coverage in 2001 was in much the same position in 2003 as a market pair that received coverage in 2004 was in 2006.

45 Other authors have also found a network effect from information technology. Röller and Waverman (2001) find that telecommunications infrastructure is associated with a positive effect on economic growth when a critical mass is achieved, whereas Brown and Goolsbee (2002) find that price dispersion for insurance policies decreases as the percentage of internet users increases.
46 Overall, the joint effect of cell phones and the interaction term is negative and statistically significant at the 5 percent level, implying that cell phones are associated with a 1.9 CFA/kg reduction in price dispersion.

Figure 3 graphs the coefficients on the dummy variables pre- and post-cell phone towers, controlling for time-varying covariates and a yearly time trend. I fail to reject the hypothesis that the OLS coefficients for the variables prior to cell phone coverage are jointly equal to zero, but I strongly reject the hypothesis that the OLS coefficients are jointly equal to zero post-treatment.[47] Consistent with the regression results, I find that price dispersion is lower in cell phone markets. This reduction is strongest in the initial 4 months' after coverage, with an average of -4.8 CFA/kg reduction in price dispersion across markets. The marginal impact decreases over time, as price dispersion in cell phone markets is -2.5 CFA/kg six months' after coverage. Since the effect does not decline significantly ten months' after coverage (the coefficient is -2.1 and statistically significant at the 10 percent level), there is little evidence that cell phone markets will return to their pre-treatment levels of price dispersion.[48]

6.3. Controlling for Selection Bias

In an effort to consistently estimate the effect of cell phones on market performance, I control for potential selection on observables by combining the DD estimation strategy with matching. I first estimate the propensity score parametrically by estimating a probit regression of the treatment on pre-treatment covariates, including variables that simultaneously influence the treatment decision and the outcome variable (Sianesi 2004, Smith and Todd 2005).[49] To provide empirical evidence that the propensity score matching approach is reasonable, I inspect the Box-Plots and histograms of the estimated propensity scores by treatment group. These show that there

[47] The F-statistic for pre-treatment dummies is F(5, 299)=.93, so we fail to reject that the OLS coefficients are jointly equal to zero. The F-statistic for the post-treatment dummies is F(6,299)=7.24, so we strongly reject the hypothesis that the post-treatment dummies are jointly equal to zero. Each of the post-treatment OLS coefficients is statistically significant at the 1 percent level. Extending the timeline to 10 months' pre and post-treatment yields similar results post-treatment.

[48] A more conventional way of testing for heterogeneous treatment effects is to run year-specific DD estimations, as outlined in equation (10). Appendix 3 shows the results of these regressions. In the initial years of cell phone coverage (Panels A-B), the impact of cell phones on price dispersion is not statistically significant. In 2003/2004, cell phones are associated with a reduction in price dispersion (Panel C), but this effect is not statistically significant. In 2004/2005 (Panel D), cell phones are associated with a negative and statistically significant reduction in price dispersion. By 2006, the impact is still negative but no longer statistically significant. These results provide evidence that a critical mass of the cell phone network occurs when over 75 percent of markets have coverage.

[49] As there is little advice available regarding the appropriate functional form for estimating propensity scores, a parsimonious probit was used. The specification included transport costs, distance, drought, road quality, market size, urban center and interaction terms.

is considerable overlap in the propensity scores of cell phone and non-cell phone market pairs (Appendix 4). In addition, the equality of means and distributions of the matched samples cannot be rejected for most of the pre-treatment covariates (not shown).

Table 6 shows the results of the pooled DD regression, correcting for selection on observables using WLS and the propensity score as an additional control.[50] The results are consistent with the unmatched samples, although the magnitude and significance of the impact of cell phones is stronger for all specifications. Cell phones are associated with a -5.7 CFA/kg and strongly significant reduction in price dispersion after controlling for yearly time dummies and market pair-specific trends (Columns 1-2), implying that price dispersion in cell phone market pairs is 26 lower than non-cell phone markets. Once monthly fixed effects are included (Columns 3-4), the magnitude of the coefficient drops, but the effect is still negative and statistically significant. Adding an interaction term between cell phones and network coverage yields similar results to the unmatched regressions (Columns 5-6).[51]

6.4. Consistency of the Standard Errors

Until now, the DD estimations have used an econometric correction with a specific functional form to correct for potential serial correlation and multi-way clustering.[52] However, Bertrand, Duflo and Mullainathan (2004) find that econometric corrections that place a specific parametric form on the time-series process do not perform well in correcting for serial correlation in DD estimates. In an effort to test the validity of the previous results, I employ a variant of the non-parametric permutation test (Efron and Tibshirani 1993, Anderson 2008). Similar to bootstrapping,

[50]Although the variance of the treatment effect should take into account the variance due to the estimation of the propensity score and the imputation of the common support, Imbens (2004) notes that there is little evidence to justify the bootstrapping approach. Consequently, standard errors in Table 6 are clustered by market pair-month, although bootstrapping was used as a robustness check.
[51]Controlling for selection bias in the year-specific DD regressions provides similar results to those in Appendix 3.
[52]Multi-way clustering assumes that if two observations are different along both of the cluster dimensions, then there is zero correlation. This implies that two different market pairs in two different time periods should have zero correlation. The regression models outlined in equations (8) and (9) can also be classified as dyadic regressions. In such regressions, robust standard errors must correct for cross-observational correlation in the error terms involving similar markets. Applying dyadic-corrected standard errors to the OLS estimates of equation (9) does not affect the magnitude of the coefficient estimate, but increases the standard errors (Fafchamps and Gubert 2007). Nevertheless, the cell phone estimates are still significant at the 5 percent level.

the procedure computes the null distribution of the test statistic under the assumptions of random assignment and no treatment effect.[53] In applying this procedure to the DD estimates in Table 3, less than 5 percent of the simulated t-statistics exceed the observed t-statistics. This suggests that the null hypothesis of no treatment effect can be rejected, thereby minimizing concerns regarding the inconsistency of the standard errors.

7. Alternative Explanations and Mechanisms

A central concern with such estimates is whether there are alternative explanations for the empirical results. Specifically, one may question the assumption of no selection on unobservables and the non-existence of general equilibrium impacts. In addition, changes in price dispersion could arise for other reasons, such as an uncompetitive market structure or changes in local supply. I first explore alternative explanations of the results before investigating the ways in which traders' behavior changes in response to the introduction of cell phones.

7.1. Selection on Unobservables

Several potential sources of unobserved bias exist, such as political pressures affecting cell phone companies' selection of cell phone markets or broader economic factors that could simultaneously affect market performance and the timing of cell phone rollout. Although the conditional independence assumption (CIA) is not directly testable, there are a number of indirect ways of assessing this (Rosenbaum 1987, Heckman and Hotz 1989, Imbens 2003). The most common approach is to estimate the treatment effect on a variable known to be unaffected by it, typically one whose value is determined prior to treatment (Imbens and Wooldridge 2007).[54] If the estimated treatment effect is close to zero, it is more plausible that the CIA holds.

[53]First, treatment assignment is randomly assigned using sampling without replacement, and the t-statistic for the difference in means is calculated. The procedure is then repeated 10,000 times, and the frequency with which the simulated t-statistics exceed the observed t-statistic is computed. If only a small fraction of the simulated t-statistics exceed the observed t-statistic, we can reject the null hypothesis of no treatment effect.

[54]A second approach, known as sensitivity analysis, explicitly relaxes the CIA (Imbens 2003).

Using this methodology, I estimate the impact of cell phones on price dispersion between 1999-2001. This is prior to the introduction of cell phones, so the outcome variable cannot be affected by the treatment. For all six tests of violations of the CIA (Table 7), the estimated effect is close to zero and not statistically significant at conventional levels. The results suggest that the CIA is plausible, and that selection on unobservables is not an overwhelming concern.[55]

7.2. General Equilibrium Effects

Until now, I have assumed that the treatment of one unit does not affect another's outcome, possibly through general equilibrium effects (Heckman, Lockner and Taber 1998). It is plausible that cell phone coverage in market pair *ij* could potentially affect price dispersion in market pair *kl*, especially if traders begin selling more of their goods in cell phone markets (a "downstream" equilibrium effect). One could also imagine a scenario whereby cell phone coverage affects the farm gate price for grains, thereby influencing farmers' production decisions and hence local supply (an "upstream" equilibrium effect).[56] Either case would potentially violate SUTVA. In this context, standard policy evaluation practices can either under- or overestimate the treatment effect.

The econometric literature on program evaluation often ignores the market consequences of treatment effects. While there is little guidance for evaluating treatment effects in a general equilibrium setting, a common approach is to combine smaller treatment units into larger units that do not interfere with one another (Rosenbaum 1987). I therefore use this approach in an attempt to address the potential "downstream" general equilibrium impacts on the treatment effect.

I first identify two regions of Niger, Zinder and Tillaberi, which are more than 900 km apart. Markets in Zinder trade primarily with Nigeria and the eastern regions of the country, whereas

[55]The correlation between the observed covariates and treatment assignment is -.03, supporting the argument that unobserved bias is of little concern.

[56]"Upstream" equilibrium effects would be a concern if cell phones had an impact upon farm-gate prices and farmers' grain production were elastic. We posit that this is not a first-order concern for two reasons. First, most grains are purchased directly from farmers in the village, and only 5 percent of villages had cell phone coverage by 2006. Second, based upon the farmer survey conducted by the author, less than 14 percent of farmers used farm-gate prices when deciding the quantity of millet to produce. This suggests that grain production is fairly inelastic.

markets in Tillaberi trade primarily with Burkina Faso and Mali. Direct trade did not occur between Zinder and Tillaberi between 2000-2006, suggesting that market pairs within these regions do not interfere with each other.[57] In addition, these regions did not receive cell phone coverage until 2003.

To assess the impact of the introduction of cell phones, I first identify treated and control markets within each region. I match cell phone market pairs within Tillaberi to non-cell phone market pairs within Zinder, and vice versa. Using these matched pairs, I estimate the DD regression with pooled treatments (Appendix 5).[58] Overall, the magnitude and statistical significance of the cell phone coefficients for these DD estimates are much stronger when compared to the estimates using all market pairs. Cell phones are associated with an 11 CFA/kg reduction in price dispersion among markets in Tillaberi as compared with non-cell phone markets in Zinder, and the effects are strongly statistically significant (Column 7). These results are robust to correcting for selection on observables using WLS and the propensity score as an additional control (Columns 8-9). This suggests that the previous analyses could have underestimated the average treatment effect.

Admittedly, this approach does not completely solve the SUTVA problem. Although I have chosen two regions that are geographically isolated, general equilibrium effects are still possible if trade occurs among markets that link the regions. I posit that these effects dissipate with distance. Furthermore, by focusing on two distinct regions, it is possible that I have introduced a new bias: different trends, which would violate a key DD assumption. I cannot reject the equality of pre-treatment trends between the regions, suggesting that this is a lower-order concern (not shown).

7.3. Collusive Behavior

[57] Trade flows are based upon data collected by the author. Trade flows within Tillaberi are based upon markets' proximity to the Niger River, whereas trade flows within Zinder are dominated primarily by markets' proximity to Nigeria.

[58] In comparing the differences in means of pre-treatment covariates between regions, none of the inter-regional differences in means are statistically different from zero. The only exception is market size; non-cell phone markets in Zinder have, on average, a larger number of traders than cell phone markets in Tillaberi. This suggests that selection on observables is not an overwhelming concern.

A final potential concern in assessing the impact of cell phone technology is whether cell phones facilitated collusive behavior among traders, specifically by facilitating communication and coordination. If the grain market structure is uncompetitive, then a reduction in price dispersion may simply be an indication of convergence towards the monopoly price. While it is difficult to test this hypothesis directly, an analysis of the grain market structure can provide some evidence of the plausibility of collusive behavior.

The most commonly used measure of market power in the agricultural marketing literature is the market concentration index, which measures the percentage of traded volume accounted for by a given number of participants (Kohls and Uhl 1985). This measure is often used as a "rule of thumb", as high concentration levels may be reasonable in light of small volumes traded.[59] Notwithstanding these caveats, I use the trader survey data to calculate the four-firm concentration ratios (CR4s) for grain markets in Niger (Figure 4). Overall, the CR4s suggest that the grain market structure is fairly competitive; nationally, the largest traders accounted for 23 percent of grain traded in 2005/2006, and 26 percent of all grain traded in 2004/2005.[60] Markets appear to be fairly competitive across regions as well, with most regions having a CR4 less than 25 percent. These results suggest that reductions in price dispersion are not driven by collusive behavior.[61]

7.4. Cell Phone Towers and Traders' Behavior

The theoretical framework of sequential search derived some partial equilibrium predictions for traders' behavior in response to a change in search costs. In order to empirically measure the impact of cell phones on traders' behavior, I estimate an equation analogous to equation (10):

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[59]Farmers in Niger also trade a large percentage of their grains via intermediaries, bypassing the grain wholesalers who are the focus of market concentration index.

[60] Kohls and Uhl (1985) suggest that a CR4 less than or equal to 33 percent is indicative of a competitive market structure, while a CR4 of 33-50 percent and above 50 percent may indicate a weak and strongly oligopolistic market structures, respectively.

[61] A related concern is whether cell phones affected traders' entry and exit in response to changes in the profitability of grain trading. Changes in the number of traders could affect overall supply to markets and hence market outcomes. The trader census data collected between 2004-2007 do not appear to support these claims.

$$Y_{ij,t} = \alpha + \beta_1 cell_{j,t} + \delta X_{ij,t} + \gamma Z_{j,t} + \theta_t + u_{ij,t} \tag{13}$$

where $Y_{ij,t}$ is the outcome of trader *i* in market *j* at time *t*, such as the number of markets over which the trader searches, the number of persons a trader consults to obtain market information, and the number of sales markets; $cell_{j,t}$ is a variable that is equal to one in all periods *t* in which a market has mobile phone access, and 0 otherwise.[62] $X_{ij,t}$ is a vector of exogenous pre-treatment regressors of trader *i* in market *j* at time *t*, including the traders' gender, age, ethnicity, years of experience, birthplace and level of education; $Z_{j,t}$ is vector of exogenous pre-treatment regressors of market *j* at time *t*, including the number of traders operating in the market, drought, road quality and whether the market is located in an urban center. θ_t is a yearly time dummy. $u_{ij,t}$ is an error term with zero conditional mean, s.t. $E[u_{ij,t} \mid cell_{j,t}, X_{ijt}, Z_{j,t}, \theta_t] = 0$, assuming that the error terms are uncorrelated with the exogenous regressors. The parameter of primary interest is β_1, where identification principally relies upon the quasi-experimental nature of the rollout of cell phones across markets and over time.[63]

Similar to the market-level identification strategy, I am concerned that differences in traders' behavior might be the result of pre-treatment characteristics that led traders to "self-select" into a cell phone market. Nevertheless, the market- and trader-level data suggest that endogenous selection into cell phone markets did not occur at the trader level. As previously discussed, the cell phone companies used specific criteria for cell phone rollout, which were not determined by nor

[62]Equation (13) defines treatment as the presence of a cell phone tower in market *j* at time *t*, rather than a traders' cell phone adoption.

[63]As all of the outcome variables in equation (13) are either binary or non-negative count variables, I use probit and Poisson maximum likelihood estimation. As the maximum likelihood estimator of the common parameters might not be consistent in panel data with *T* observations and individual fixed effects, the probit specifications do not include fixed effects. We also adjust the Poisson MLE standard errors in the event that Poisson distributional assumption is not valid. OLS estimates are also provided as a rough comparison.

strongly correlated with market or trader characteristics. Empirical tests conducted throughout this paper suggest that selection bias is not an overwhelming concern at the market level.

Furthermore, traders' "self-selection" into cell phone markets does not seem likely. Based upon trader censuses conducted between 2004-2007, the number of traders per market did not vary significantly on an intra- or inter-annual basis.[64] This coincides with the period of significant expansion in cell phone coverage, and one during which I would expect to find trader "sorting" if it were to occur. Second, according to the trader-level data, only 10 percent of all traders surveyed changed their principal (home) market since they began trading (Table 1). Compared to average number of years of experience (16 years), this suggests that traders do not quickly or easily change their principal markets. This is not surprising, as most traders operate in the market that is the closest to their village. Among those traders who did change their principal market, there is no statistically significant difference in means between traders located in cell phone and non-cell phone markets. In fact, a higher percentage of traders relocated to a market without a cell phone tower.

The trader survey data appear to support these claims. Table 8 presents the differences in means and distributions of pre-treatment covariates for traders located in cell phone and non-cell phone markets.[65] Surprisingly, none of the differences in means for trader-level covariates are statistically different from zero. The results are similar using an alternative definition of the pre-treatment year. In looking at market-level covariates (Panel B), I also cannot reject the equality of means for most of the covariates, with the exception of market size and the market's location in an

[64] A trader census was conducted on each market during the 2005/2006 and 2006/2007 marketing seasons, with retrospective data for 2004/2005. There was a moderate amount of entry and exit during this time, from 3,320 traders in 2004/2005 to 3,342 traders in 2005/2006 and 3,345 in 2006/2007. There does not appear to be a correlation between the number of traders per market and the introduction of cell phones in that market.

[65] The correct definition of the pre-treatment year is 2001, prior to the date when any of the markets were treated. However, the trader-level data dates from 2004. To address this issue, I first compare markets treated in 2005 with those that were never treated. For this subsample, the pre-treatment year is defined as 2004. Using 2004 as the pre-treatment year drops seven markets and over 75 percent of our sample size, as several large markets received cell phone coverage in 2003 and 2004. As an alternative, I use all markets, but restrict the sample to those traders with more than 2 years' of experience. In this case, the time-invariant covariates are still valid as pre-treatment covariates. I posit that changes in most of the relevant time-variant covariates between 2003 and 2004 are highly unlikely.

urban center. Overall, these results suggest that selection on observables is not a first-order concern.

Controlling for pre-treatment trader and market-level characteristics, the effect of cell phone towers on traders' behavior appears to be substantial. Table 9 presents the regression results of equation (13) using OLS (Column 1), Poisson (Column 2), probit (Column 3) and propensity score matching (Column 4). Traders in cell phone markets search in .91 more markets, implying a 26 percent increase as compared to traders located in non-cell phone markets (Column 1). This confirms the theoretical prediction that a reduction in search costs leads to an increase in the expected number of markets over which traders search. The Poisson coefficient is also positive and statistically significant (Column 2), suggesting that cell phone coverage is associated with a 22 percent increase in the number of markets over which traders search. Cell phone coverage is also associated with an increase in traders' contacts; the OLS coefficient suggests that traders in cell phone markets consult 1.5 more people for market information as compared to their non-cell phone counterparts.[66] Finally, OLS estimates suggest that traders in cell phone markets are 7 percent more likely to rely upon their personal and professional contacts for market information. Probit estimates support this finding.

Cell phone towers not only appear to affect traders' search behavior, but also where traders buy and sell grains. Traders in cell phone markets are 8 percent more likely to change their sales markets inter-annually, although the coefficient estimate is only marginally statistically significant for the probit regression. In addition, traders in cell phone markets appear to buy and sell in a larger number of markets; the OLS estimates suggest that traders in cell phone markets sell in one additional market as compared to their non-cell phone counterparts. Considering that grain traders in non-cell phone markets trade in an average of 4 markets per year, one market represents a 25

[66] The Poisson coefficient suggests that the expected number of persons that traders' consult is 33 percent higher in cell phone markets.

percent increase. This is supported by the Poisson regression, which suggests that the expected number of sales and purchase markets is 22 percent higher for traders in cell phone markets. All of these results are robust to the use of propensity score matching (Column 4).

The small percentage of traders who change their principal markets suggests that there is not a selection on observables problem. Nevertheless, there could still be unobserved covariates that affect treatment assignment and traders' behavior simultaneously. If traders who moved into cell phone markets are more intelligent or have larger social networks, then these unobserved factors could lead to an overestimation of our treatment effect. If, however, traders who moved into non-cell phone markets are more adept at trading, then this could lead to an underestimation of our treatment effect.

To address the potential selection problem, I can either explicitly model the process determining selection (Heckman 1979), or construct bounds on the treatment effect (Manski 1990, Rosenbaum 2002, Lee 2005). I adopt the latter approach, calculating upper and lower bounds for differential selection by trimming the distribution (Lee 2005, Blattman and Annan 2007).[67] I first construct the "best-case" bound by dropping traders in cell phone markets with lower values of the outcome, and then calculating the 'trimmed' treatment effect. The "worst-case" bound is calculated by dropping the "best-performing" traders in cell phone markets.

Bounds for each outcome are provided in Table 10. Lee's approach compares the untrimmed treatment effect (Column 1) to the upper and lower bounds (Columns 2 and 3). In general, the treatment effects under the "best-case" scenario are greater than the untrimmed treatment effects, and equally robust. The treatment effects under the "worst-case" scenario are generally smaller than the untrimmed treatment effects, but statistically significant. The results

[67] Lee's method is used for selective attrition, trimming the distribution of the outcome in the group with less attrition. Blattman and Annan (2007) apply this to deal with attrition in groups of abductees in Uganda. Analogous to this approach, I trim the distribution of the outcome of the group with less selection – in this case, traders in cell phone markets. I also trim the distributions of the outcomes by dropping traders in cell and non-cell phone markets who changed their principal market to construct best- and worst-case scenarios.

suggest that even under strong trader selection, cell phone towers still have a statistically significant effect on traders' behavior.

8. Cell Phone Coverage and Welfare Effects

The previous results suggest that there are potential welfare improvements associated with the introduction of cell phones in Niger, primarily due to a more efficient allocation of grains across markets. Nevertheless, the net welfare gains, and how such gains are distributed among farmers, traders and consumers, are ambiguous. To provide a simple estimate of welfare changes, I first assess the impact of cell phones on consumer grain prices between 2001-2006. I then measure the impact of cell phones on traders' profits. As a majority of farm households in Niger are net buyers of millet,[68] these analyses provide an indication of the net welfare gains of information technology.

In order to estimate the effect of cell phones on consumer welfare, I first examine the change in consumer prices for millet.[69] Assume that each consumer has a quasilinear and concave utility function, with $u(q)+y$, where q is the homogenous good (millet) that the consumer wishes to buy, and y is the numeraire good. This implies that the indirect utility function of a consumer with an income of M who pays a price of p per unit of millet is $V(p,M)=v(p)+M$, where $V(p,M)$ is non-increasing in p.

Table 11 shows the results of the DD regressions using consumer retail prices as the dependent variable (Column 1). On average, the introduction of cell phones is associated with a 3.6 CFA/kg reduction in consumer prices, representing a 3 percent reduction relative to the pre-treatment price in non-cell phone markets. During the 2005 food crisis, the presence of a cell phone tower was associated with a 9.6 CFA/kg reduction in consumer prices.[70] As the mean grain price in

[68] Based upon the farmer survey conducted by the author. Over 90 percent of farm households surveyed were net buyers of millet during the 2004/2005 and 2005/2006 marketing seasons.
[69] Wright and Williams' (1988) framework for analyzing the welfare effects of price stabilization cannot be applied to this case.
[70] Niger experienced a severe food crisis in 2005. Grain prices represented 27 percent of per capita income, and were 8 percent higher in food crisis regions as compared to non-crisis regions (Aker 2008). In order to consistently estimate the effect of cell phones on

untreated markets was 212 CFA/kg, this implies that grain prices in cell phone markets were 4.5 percent lower.

Although the change in consumer welfare is more than the change in consumer price, I do not have the data to undertake a full welfare analysis. Consequently, I provide a rough approximation. Prior to the introduction of cell phones, consumers faced an intra-annual distribution of millet prices, $F(p) \sim p_F, \sigma_F^2$. After the introduction of cell phones, consumers faced a distribution of $G(p) \sim p_G, \sigma_G^2$, where $p_F > p_G, \sigma_F^2 > \sigma_G^2$. This suggests that $\int_0^{\bar{p}} G(p)dp \leq \int_0^{\bar{p}} F(p)dp$ $\forall p \in [0, \infty]$, implying that *G(p)* second-order stochastically dominates *F(p)*.[71] Consequently, risk-averse, expected utility-maximizing consumers would prefer *G(p)*.

More concretely, lower relative grain prices in cell phone markets could have increased the quantity of millet consumed by rural households. Using an own-price elasticity of demand of -.52,[72] lower grain prices in cell phone markets would have increased quantity demanded by an additional 4 kg per capita per year. All else equal, this would have resulted in an additional eight days' worth of millet consumption for adults, and twelve days' worth of consumption for children between the ages of 2 and 5.[73] The magnitude of this effect was stronger in 2004/2005, suggesting that the presence of cell phone towers could have reduced the severity of the food crisis.

To further disentangle the net welfare effects, I also measure the impact of cell phones on traders' profits. Assuming that the introduction of cell phones will affect traders' revenues (sales prices and total quantity sold) and costs (mobile phone calls and decreased travel), Table 11 shows the effects of the introduction of cell phones on traders' profits, controlling for individual and

consumer prices during the food crisis, I match cell phone and non-cell phone markets in food crisis regions in 2004/2005. This allows us to determine whether, for given market conditions in 2004/2005, cell phone towers were associated with lower consumer prices.

[71] A graphical analysis of the density functions of grain prices by cell phone coverage supports these assumptions.

[72] Subhan (2004) estimates that the own-price elasticity of demand for millet in Niger is -.52 and the income elasticity of demand is .64.

[73] While this magnitude seems small, children can become severely malnourished within a 7-day period.

market-specific effects. Cell phones increased the annual quantity sold by traders, although this effect is not statistically significant (Column 2). This suggests that cell phone towers did not induce an increase in the quantity supplied. By contrast, the average sales price received by traders in cell phones markets increased by 9 CFA/kg, and this effect is strongly statistically significant (Column 3). Column 4 shows that the net effect of these changes is an increase in average daily profits by 258 CFA, equivalent to an additional USD $182 per year. This represents a 29 percent increase as compared to traders' profits in non-cell phone markets during the pre-treatment period.

9. Conclusions

This paper provides some estimates of the nature, magnitude and distribution of the effects of cell phones on grain market performance and welfare in Niger. The introduction of cell phones is associated with a 22 reduction in price dispersion across grain markets, with a larger impact over time and for those market pairs with higher transport costs. The primary mechanism through which cell phones affect market-level outcomes appears to be a reduction in search costs, as grain traders operating in cell phone markets search over more markets and sell in more markets.

More broadly, this paper provides empirical evidence of the importance of information for market performance, suggesting that the "I" is more important than the "T". Information provision is therefore necessary but not sufficient for welfare improvements, especially in the presence of other market failures. Nevertheless, cell phones appear to be a particularly effective and low-cost means of providing such information, and are well-suited to social and commercial norms in sub-Saharan Africa. The technology may also be sustainable, as it has been adopted by grain traders.

These issues are central to the current debate concerning the role of information technology in promoting economic development. Information technology is often considered to be a low development priority when compared to other basic needs. While basic needs should not be overlooked, cell phones can be an effective poverty reduction tool for poor rural households and host country governments. Consequently, political and financial support for information technology hardware (infrastructure) and software (pricing schemes) could be warranted.

In order to generalize these results beyond Niger, some final words of interpretation on the treatment effects are necessary. The fact that the counterfactual might be affected by cell phone coverage in other markets is a potential source of bias that I cannot address. Since cell phones appear to affect traders' behavior, they could reduce the quantity of grains supplied to non-cell phone markets. Although this paper attempted to estimate the treatment effect in light of SUTVA violations, there is a possibility that the treatment effect might be overestimated.

Finally, while these results suggest there have been average welfare gains associated with the introduction of cell phones in Niger in the short-term, it is possible that traders' profits could decrease in the longer-term, especially as price differences approach transaction costs. In addition, as I have not undertaken a full welfare analysis for farmers, how these gains are shared among farmers, traders and consumers is ambiguous. Nevertheless, as the average farm household is net consumer of millet in Niger, the results suggest that the introduction of cell phones is potentially Pareto-improving.

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Table 1. Description of Key Variables: Grain Trader and Market Baseline Characteristics

Variable Name	Sample Mean (s.d.)	# of obs
Panel A: Trader-Level Characteristics		
Socio-Demographic Characteristics		
Ethnicity		395
Hausa	0.65	255
Zarma	0.17	65
Other	0.18	75
Age	45.71(12.2)	395
Gender(male=0, female=1)	0.11(.32)	395
Education (0=elementary or above, 1=no education)	0.62(.48)	395
Trader type		395
Wholesaler	0.17	67
Semi-wholesaler	0.15	61
Intermediary	0.15	61
Retailer	0.53	206
Years' of Experience	16.0(10.2)	395
Commercial Characteristics		
Engage in trading activities all year round	.94(.22)	395
Trade in agricultural output products only	0.98(.02)	395
Engage in activities outside of trade	0.92(.28)	395
Co-ownership of commerce	.19(.40)	395
More than 75 percent of commerce sold in principal market	.59(.49)	395
Changed "principal market" since he/she became a trader	.10(.31)	395
Number of markets where trade goods	4.42(2.84)	395
Number of markets where follow prices	3.87(3.0)	395
Number of days of storage	7.14(9.8)	395
Own cell phone	.29(.45)	395
Own means of transport (donkey cart, light transport)	.11(.32)	395
Panel B. Market-Level Characteristics		
Type of market		35
Collection	0.19	7
Wholesale	0.36	13
Retail	0.30	10
Border	0.15	5
Number of traders	137(99.6)	35
Road quality (1=paved road, 0=otherwise)	.71(.45)	35
Market located more than 50 km from paved road	.07(.26)	35
New paved road in past 5 years	.15(.37)	35
Located in an urban center (>35,000 people)	.39(.48)	35
Cell phone coverage 2005/2006	.78(.41)	35
Cell phone coverage 2004/2005	.62(.48)	35
Drought in 2004/2005	.40(.49)	35
Food crisis region in 2004/2005	.38(.48)	35

Notes: Data from the Niger trader survey collected by the author. Sample means are weighted by inverse sampling probabilities.

Table 2. Comparison of Observables by Treated and Untreated Groups in the Pre-Treatment Period (1999-2001)

Pre-Treatment Observables	Unconditional Mean				Difference in Means	Difference in Distributions	
	Cell Phone		No Cell Phone		Unconditional	Unconditional Kolmogorov-Smirnov Test	
	Mean (s.d.)	Obs	Mean (s.d.)	Obs	s.e.	D-statistic	p-value
Panel A. Market Pair Level Data							
Price dispersion between markets (CFA/kg)	20.72 (16.9)	6274	22.14 (16.49)	1142	-1.73 (1.92)	0.0803***	0
Distance between markets (km)	377.3 (217.5)	10296	378.64 (227.65)	2640	-.447 (24.8)	0.0638	0.712
Road Quality between markets	0.418 (.493)	10296	.318 (.465)	2640	.100*(.052)	0.1003	0.331
Market Size	0.074(.262)	10296	.082(.274)	2640	-.008(.029)	0.008	1
Drought in 1999 or 2000	.013(.114)	10296	.019 (.137)	2640	-.006(.004)	0.006	1
Urban center(>=35,000)	0.169 (.374)	10296	0.000 (.001)	2640	0.169***(.020)	0.169**	0.018
Transport Costs between Markets (CFA/kg)	12.73 (6.89)	10296	12.74 (7.12)	2640	0.013 (.771)	0.052***	0
Panel B. Market Level Data							
Price level (CFA/kg)	128(34.18)	648	115.22(35.3)	96	12.84(8.13)	0.375***	0
Road Quality to Market	0.629(.483)	648	.5(.5)	96	.129(.271)	0.129	0.12
Market Size	103.11(79.65)	648	101.75(45.5)	96	1.361(27.8)	0.379***	0
Drought in 1999 or 2000	.021(.143)	648	.025(.156)	96	-.004(.014)	0.004	1
Urban center(>=35,000)	0.407(.491)	648	0(.00)	96	.407***(.096)	0.407***	0

Notes: Data from the Niger trader survey and secondary sources collected by the author. In Panel A, "cell phone" market pairs are pairs where both markets received cell phone coverage at some point between 2001-2006; "no cell phone" market pairs are those pairs where either one or both markets never received cell phone coverage. The number of market pairs is 433. In Panel B, "cell phone" markets are those that received coverage at some point between 2001-2006, whereas "no cell phones" markets are those markets that never received coverage. The number of markets is 31. Huber-White robust standard errors clustered by market pair-month (Panel A) and by market-month (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. The Kolmogorov-Smirnov test tests for the equality of the distribution functions.

Table 3. Estimated Effects of Cell Phone Coverage on Price Dispersion: DD Estimation with First Differences

Dependent variable	(1) P_{it}-P_{jt}	(2) Coefficient of Variation	(3) P_{it}-P_{jt}	(4) Coefficient of Variation	(5) P_{it}-P_{jt}	Arellano-Bond GMM Estimator	(7) P_{it}-P_{jt} Arellano-Bond GMM Estimator
Cell Phone Dummy (both treated)	-4.65*** (1.06)	-.039* (.020)	-4.77*** (1.06)	-.039* (.020)	-4.42*** (1.06)	-1.87** (.938)	-1.93** (.943)
Transport costs (CFA/kg)	.650*** (.139)		.653*** (.141)		.782*** (.142)	.670*** (.149)	.691*** (.145)
Drought Dummy	1.64*** (.445)	.001 (.001)	1.74** (.447)	.001 (.001)	1.58*** (.448)	.419 (.468)	.428 (.468)
Gas prices (CFA/kg)		-.0001*** (.000)		-.0001*** (.000)			
Lagged dependent variable						-.006 (.025)	-.006 (.025)
Constant	0.827*** (.079)	.000 (.000)					
Common Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group-specific time trend	No	No	Yes	Yes	Yes	No	No
Market-Pair Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly time dummy	No	No	No	No	Yes	No	Yes
# of observations	27342	2393	27342	2393	27342	25942	25942
# of cross-sectional observations	433	31	433	31	433	433	433
R^2	0.0075	0.0885	0.0075	0.0879	0.0086		
Joint effect						-1.86** (.93)	-1.92** (.935)
Pre-treatment value of dependent variable for control groups	22.14	0.312	22.14	0.312	22.14	22.14	22.14

Notes: Data from the Niger trader survey and secondary sources collected by the author. For market pairs, cell phone dummy =1 in period *t* when both markets have cell phone coverage, 0 otherwise. For markets, cell phone dummy =1 when the market has cell phone coverage in time *t*, 0 otherwise. Drought dummy=1 in period *t* when a market has rainfall less than or equal to 2 standard deviations below its average rainfall level during the rainy season, or 15 consecutive days without rainfall during the rainy season, 0 otherwise. Huber-White robust standard errors clustered by market pair-month (price difference) and market-month (CV) are in parentheses. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are deflated by the Nigerien Consumer Price Index (CPI).

Table 4. Variation in Treatment Effect of Cell Phones by Gas Prices, Inter-Market Distance and Road Quality

Dependent Variable: ***Price dispersion at time t***

	(1)	(2)	(3)	(4)	(5) Short Haul (<100 km)	(6) Medium Haul (100-550km)	(7) Long Haul (>550km)	(8)	(9) Both or One Unpaved	(10) Both Paved
Cell Phone Dummy	-4.42*** (1.03)	-4.17** (1.02)	-2.97** (1.22)	-2.60** (1.22)	-2.81 (2.81)	-4.18** (1.23)	1.55 (2.28)	-.399 (.852)	-7.30*** (1.71)	-.077 (.847)
Cell*Gas price (CFA/kg)	-.389 (.521)	-.386 (.524)								
Cell*Distance Dummy			-4.07* (2.17)	-4.09* (2.17)						
Cell*Road Quality (unpaved road==1)								-7.15*** (1.89)		
Transport Costs	.659*** (.141)	.792*** (.144)	.652*** (.141)	.786*** (.142)	1.93 (2.35)	.886*** (.189)	.759** (.215)	.776*** (.142)	.918*** (.179)	1.41*** (.428)
Drought dummy	1.65*** (.445)	-1.58** (.625)	1.66*** (.445)	1.59*** (.447)	1.57 (1.21)	.844* (.513)	4.50*** (1.01)	-1.61*** (.446)	2.83*** (.544)	-.586 (.763)
Constant	.816*** (.080)									
Common Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group-specific time trend	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market-Pair Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly time dummy	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of observations	27342	27342	27342	27342	2176	20079	5087	27342	15019	12323
# of cross-sectional observations	433	433	433	433	35	318	80	433	262	171
R^2	0.008	0.0087	0.008	0.0088	0.0073	0.0084	0.0135	0.0096	0.0118	0.0061
Joint effect	-5.52*** (1.42)	-4.97*** (1.43)	-7.05*** (1.81)	-6.69*** (1.79)				-4.74*** (1.09)		
Pre-treatment value of dependent variable for control groups	22.14	22.14	22.14	22.14	22.14	22.14	22.14	22.14	22.14	22.14

Notes: Data from the Niger trader survey and secondary sources collected by the author. Huber-White robust standard errors clustered by market pair-month 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. The results in Columns 3-10 are similar without group-specific time trends. The Chow test for the equality of the coefficients across the split samples for distance (Columns 5-7) is F(9,432)=15.55, allowing us to reject the equality of the coefficients across samples. The Chow test for the equality of the coefficients across the split samples for road quality (Columns 9-10) is F(11, 432)=5.34, allowing us to reject the equality of the coefficients.

Table 5. Treatment Effect Heterogeneity over Time: Network Effects

Dependent variable	(1) $P_{it}-P_{jt}$	(2) CV	(3) $P_{it}-P_{jt}$	(4) CV
Cell Phone Dummy	.652 (1.11)	.011 (.029)	.509 (1.09)	.011 (.029)
Cell Phone Dummy*Network	-11.75*** (2.69)	-.104*** (.033)	-10.37*** (2.57)	-.104*** (.033)
Transaction costs	.665*** (.143)		.783*** (.140)	
Drought	1.82*** (.452)	.001 (.001)	1.55*** (.449)	.001 (.001)
Constant				
Common Time Trend	Yes	Yes	Yes	Yes
Group-specific time trend	No	No	Yes	Yes
Market-Pair Fixed effects	Yes	Yes	Yes	Yes
Yearly time dummy	Yes	Yes	Yes	Yes
Monthly time dummy	No	No	Yes	No
# of observations	27342	2393	27342	2393
# of cross-sectional observations	433	31	433	31
R^2	0.008	0.1147	0.0091	0.1147
Joint effect	-1.87** (.942)	-0.092*** (.022)	-1.36 (.914)	-0.092*** (.022)
Pre-treatment value of dependent variable for control groups	22.14	0.312	22.14	0.312

Notes: Data from the Niger trader survey and secondary sources collected by the author. For market pairs, "cell phone dummy"=1 in period *t* when both markets have cell phone coverage, 0 otherwise. For markets, "cell phone dummy"=1 when the market has cell phone coverage in time *t*, 0 otherwise. "Drought dummy"=1 in period *t* when a market has rainfall less than or equal to 2 standard deviations below its average rainfall level during the rainy season, or 15 consecutive days without rainfall during the rainy season, 0 otherwise. "Network" is a variable measuring the percentage of market pairs with cell phone coverage at time t. Huber-White robust standard errors clustered at the market pair level (price difference) and the market level (CV) are in parentheses. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are deflated by the Nigerien Consumer Price Index.

Table 6. DD Estimates of Cell Phone Coverage Effects on Price Dispersion: Matching Results

Dependent Variable: ***Price dispersion between markets at time t***

	(1) WLS	(2) Propensity Score	(3) WLS	(4) Propensity Score	(5) WLS	(6) WLS
Cell Phone Dummy	-5.77*** (1.30)	-5.70*** (1.29)	-5.44*** (1.29)	-5.37*** (1.28)	-1.85 (1.78)	-1.65 (1.75)
Cell Phone Dummy*Network					-10.50** (4.36)	-10.14** (4.25)
Constant trend	Yes	Yes	Yes	Yes	Yes	Yes
Group trend	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Dummy	No	No	Yes	Yes	No	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
# of Observations	23062	23062	23062	23062	23062	23062
# of Cross-sectional Obs	433	433	433	433	433	433
R^2	0.01	0.01	0.103	0.104	0.08	0.103
%Δ	-26.05%	-25.73%	-24.57%	-24.24%	-15.49%	-11.06%
Joint effect (cell and network):					-3.43** (1.39)	-3.18** (1.37)

Notes: Data from the Niger trader survey and secondary sources collected by the author. "Cell phone dummy" =1 in period *t* when both markets have cell phone coverage, 0 otherwise. "Network" is a variable measuring the percentage of market pairs with cell phone coverage at time *t*. All regressions include controls for transport costs, drought and gas prices. Huber-White robust standard errors clustered by market pair-month are in parentheses. Standard errors were also bootstrapped to take into account the parametric estimation of the propensity score; results are available upon request. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are deflated by the Nigerien Consumer Price Index.

Table 7. Tests of the Conditional Independence Assumption

Dependent Variable: ***Price Dispersion in 1999-2001 (Pre-Treatment)***

Estimation Method	**Coeff(s.e.)**	**T-statistic**
Unconditional difference in means	-.117 (2.12)	-0.05
Conditional difference in means	.126 (1.92)	0.07
Propensity score regression	-.987 (2.01)	-0.49
Propensity score regression with demeaned propensity score	-.987 (2.02)	-0.49
Weighting and regression	.669 (1.20)	0.56
Weighting and regression with additional covariates	1.65 (1.03)	1.6

Notes: Data from the Niger trader survey and secondary sources collected by the author. Cell phone dummy =1 for those market pairs that ever received cell phone coverage between 2001-2006, 0 otherwise. Huber-White robust standard errors clustered by market pair-month are in parentheses. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are deflated by the Nigerien Consumer Price Index.

Table 8. Comparison of Trader-Level and Market-Level Covariates in Pre-Treatment Years

Pre-Treatment Covariates	Cell Phone Markets Mean(s.d.)	Non-Cell Phone Markets Mean(s.d.)	Difference in Means Unconditional T-C (s.e.)	Difference in Distributions Unconditional K-S Test D-statistic (p-value)
Panel A. Trader-Level Characteristics				
Gender	.126(.333)	.058(.235)	.068(.06)	.068(.914)
Education (0=elementary or above, 1=no education)	.608(.488)	.663(.475)	-.054(.08)	.054(.989)
Age	46.01(12.6)	44.60(10.75)	1.41(1.64)	.081(.777)
Hausa ethnic group	.656(.475)	.605(.491)	.052(.162)	.052(.993)
Years of Experience	16.21(10.28)	15.33(9.68)	.880(1.83)	.096(.566)
Changed Principal Market since became trader	.097(.296)	.146(.355)	-.049(.044)	.049(.998)
Co-ownership of business	.185(.389)	.241(.430)	-.055(.050)	.055(.988)
Wholesaler or semi-wholesaler	.312(.463)	.372(.486)	-.061(.074)	.061(.962)
Storage capacity (MT)	88.02(340.2)	105.07(231.35)	-17.05(37.29)	.092(.713)
Number of storage units	1.67(2.06)	2.17(2.82)	-.500(.306)	.119(.299)
Trade all year	.951(.215)	.895(.307)	.056(.040)	.056(.984)
Have bank account	.138(.345)	.099(.300)	.034(.039)	.039(.999)
Own means of transport (donkey cart, light transport)	.106(.309)	.139(.348)	-.032(.039)	.032(1.00)
Number of employees (family and non-family)	3.84(3.84)	3.97(3.22)	-.132(.458)	.060(.968)
Member of traders' association	.345(.476)	.296(.459)	.048(.073)	.049(.998)
Panel B. Market-Level Characteristics				
Distance to paved road greater than 75km	.045(.208)	.015(.36)	-.106(.116)	.106(.438)
Road quality	.359(.305)	.686(.495)	.326(.307)	.326(.31)
New paved road over the past 5 years	.186(.390)	.114(.318)	.073(.143)	.073(.708)
Number of traders	151.17(106)	86.67(37.14)	64.49*(32.7)	0.395(.000)
Drought in 2004	.388(.488)	.453(.500)	-.065(.219)	.065(.938)
Drought in 2000	0.317(.466)	.5(.502)	-.182(.217)	.182**(.022)
Urban center	.501(.501)	0	.502***(.122)	.502***(0.00)

Notes: Data from the Niger trader survey and secondary sources collected by the author. "Cell phone" markets are those that received coverage at some point between 2003-2006, whereas "no cell phones" markets are those markets that never received coverage. N=395 traders, 35 markets Huber-White robust standard errors clustered by market are in parentheses. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. The Kolmogorov-Smirnov test tests for the equality of the distribution functions.

Table 9. Estimated Effects of Cell Phone Towers on Traders' Behavior

Dependent variable:	(1) OLS Estimate		(2) Poisson QMLE Estimate		(3) Probit MLE Estimate	(4) Nearest Neighbor Matching Estimate	
	Coeff (s.e.)	%Δ	Coeff (s.e.)	Coeff (adj s.e.)	Coeff (df/dx) (s.e.)	Coeff (s.e.)	%Δ
# of Markets Searched	.91** (.46)	26.26%	.22** (.11)	.22** (.05)		.91** (.47)	26.49%
# of people consulted for market information	1.5*** (.50)	39.95%	.33*** (.11)	.33** (.08)		1.7*** (.71)	45.14%
Use personal contacts to obtain market information	.07*** (.02)	7.99%			.61*** (.09)	.07* (.04)	7.57%
Change sales markets (Yes=1, 0=No)	.08 (.06)	57.14%			.08* (.05)	.09* (.05)	64.29%
# of Purchase and Sales Markets	1.02** (.71)	25.37%	.22** (.09)	.22*** (.02)		1.13* (.70)	28.04%

Notes: Data from the Niger trader survey and secondary sources collected by the author. Each entry represents a separate regression. Controls in the OLS, Poisson and probit regression include pre-treatment trader and market characteristics. Weighted by inverse sampling probability. "Cell phone" dummy is a binary variable equal to 1 if the market had cell phone coverage in 2005, 0 otherwise. Huber-White robust standard errors clustered by market are in parentheses for the OLS estimates. "adj s.e." refers to robust standard errors corrected for heteroskedasticity, clustering and Poisson regression (underdispersion) are in parentheses for the Poisson estimates. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level.

Table 10. Treatment Effect Bounding for Endogeneous "Sorting" into Cell Phone Markets

Dependent variable:	(1) Untrimmed ATE	(2) "Best case" Bound	(3) "Worst Case" Bound
# of Markets Searched	.83**(.42)	.99**(.41)	.83**(.42)
# of people consulted for market information	1.4**(.7)	1.6**(.62)	1.4**(.7)
Use personal contacts to obtain market information	.06***(.03)	.06**(.02)	.06**(.03)
Change sales markets	.06**(.03)	.08**(.04)	.05*(.03)
# of Purchase and Sales Markets	.80*(.46)	.95**(.31)	.67*(.31)

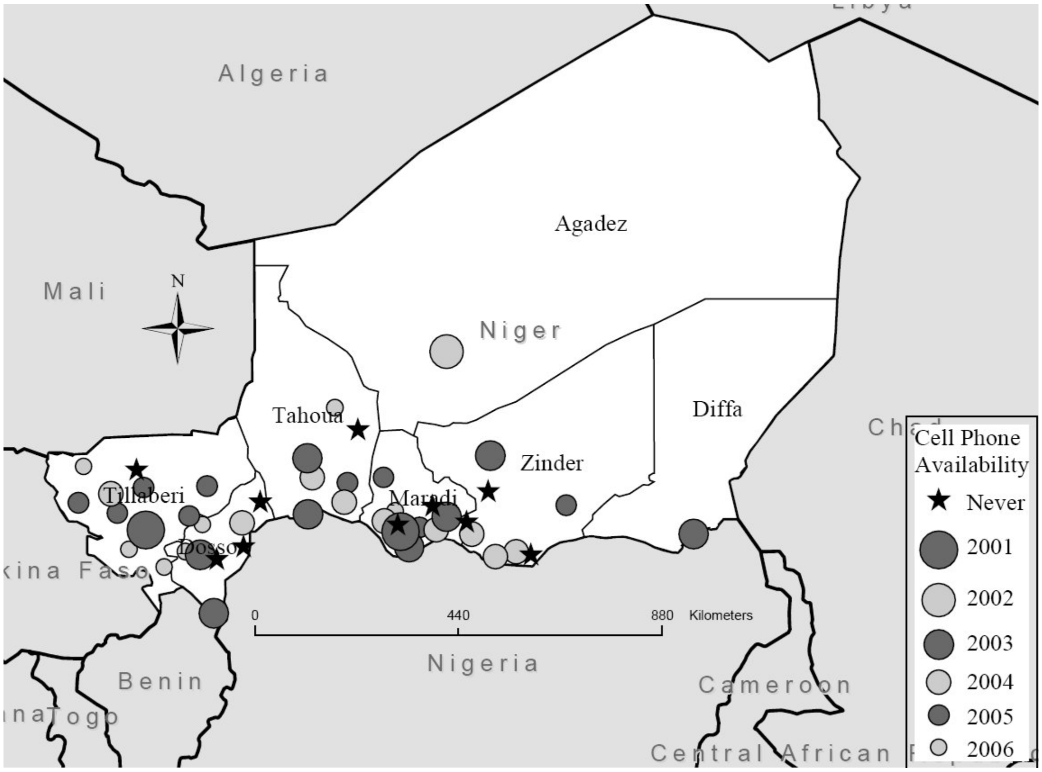
Notes: Data from the Niger trader survey and secondary sources collected by the author. "Cell phone" dummy is a binary variable equal to 1 if the market had cell phone coverage in 2005, 0 otherwise. The untrimmed treatment effect is the difference in the weighted means of traders in cell phone and non-cell phone markets, and is not a regression estimate. No controls are used. Best and worst-case bounds are calculated as the difference in the weighted means of traders in cell phone and non-cell markets after 'trimming' the top or the bottom of the distribution of the outcome variable in the treatment group that has moved less frequently (ie, traders in cell phone markets). They are not regression estimates. Huber-White robust standard errors clustered by market are in parentheses. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level.

Table 11. Estimated Effects of Cell Phone Coverage on Traders and Consumers

Dependent variable	(1) Consumer Price (CFA/kg)	(2) Quantity Sold by Traders (kg)	(4) Price Received by Traders (CFA/kg)	(5) Traders' Profit (CFA)
	-3.65*	177.26	9.96***	258.5**
Cell Phone Dummy	(1.92)	(1563.5)	(1.97)	(111.44)
Group-specific time trend	Yes	Yes	Yes	Yes
Market Fixed Effect	Yes	Yes	Yes	Yes
Yearly time dummy	Yes	Yes	Yes	Yes
Monthly time dummy	Yes	No	No	No
# of observations	2209	395	395	395
# of cross-sectional observations	31	31	31	31
R^2	0.6503	0.1495	0.1489	0.1489
Percentage change	-3.17%	5.09%	6.78%	29.00%
Pre-treatment value of dependent variable for control groups (CFA)	115.2(35.3)	3480.4(714.8)	148.0(26.3)	200.7(442.4)

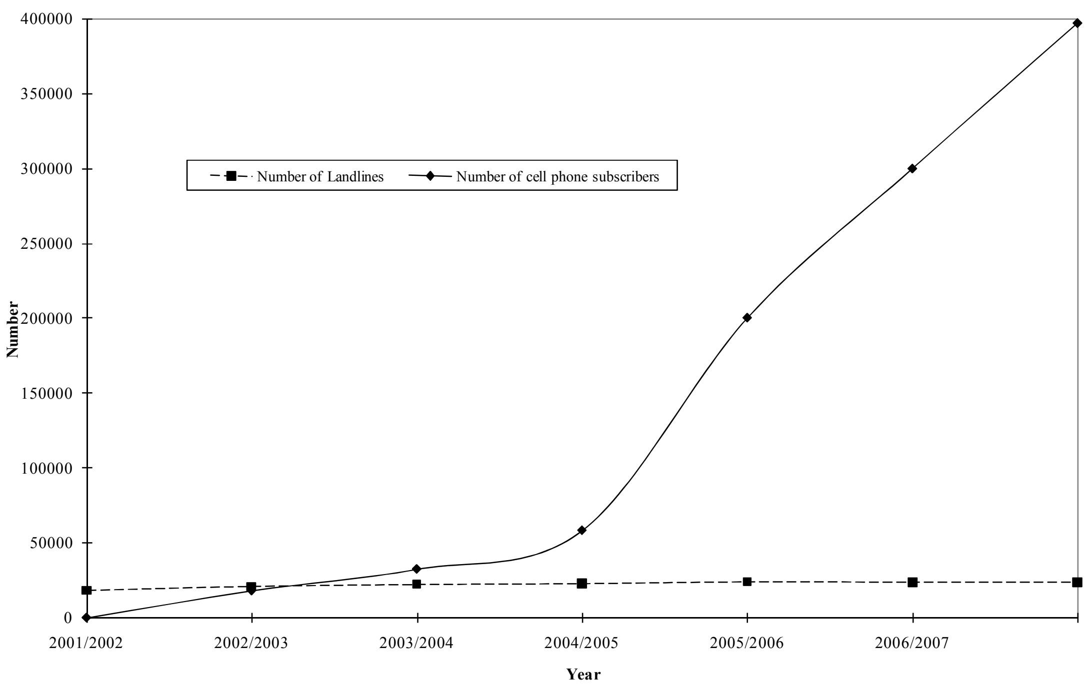
Notes: Data from the Niger trader survey and secondary sources collected by the author. Cell phone dummy =1 when the market has cell phone coverage in time *t*, 0 otherwise. Drought dummy=1 in period *t* when a market has rainfall less than or equal to 2 standard deviations below its average rainfall level during the rainy season, or 15 consecutive days without rainfall during the rainy season, 0 otherwise. Huber-White robust standard errors clustered by market-month are reported for Columsn 1 and 2. Huber-White robust standard errors cluster by market and correcting for sampling weighing are reported for Columns 3-5. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are deflated by the Nigerien Consumer Price Index.

Figure 1. Cell Phone Coverage by Market and Year, 2001-2006



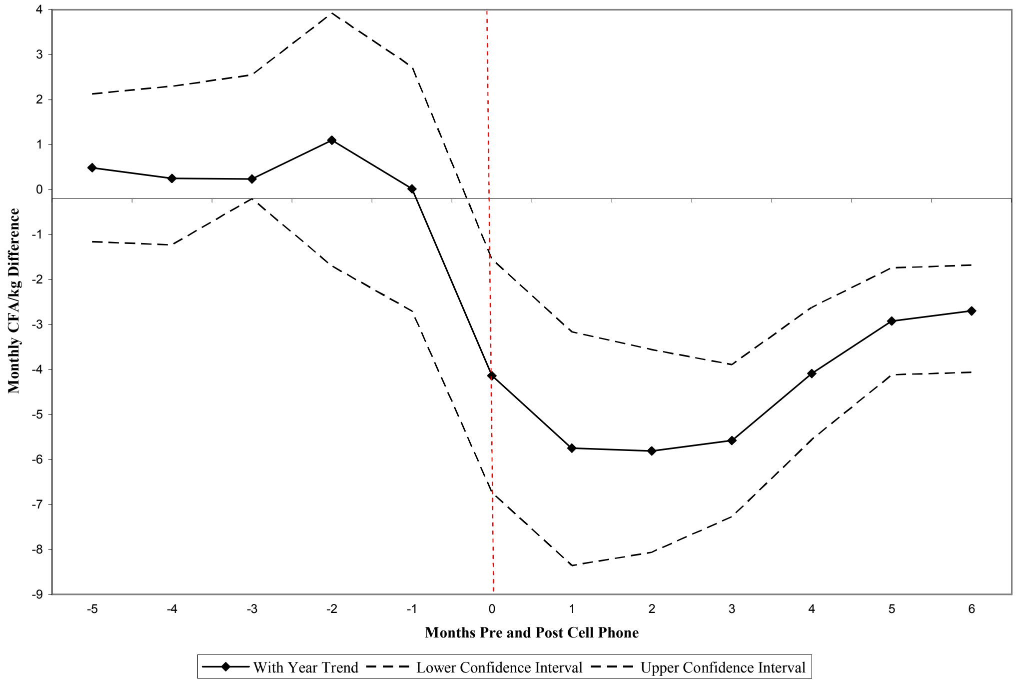
Notes: Data collected by the author from cell phone companies in Niger (Celtel, Telecel and Sahelcom). The map shows cell phone coverage for grain markets between 2000-2006, but not all towns and cities in Niger.

Figure 2. Number of Cell Phone Subscribers and Landlines in Niger, 2000-2006



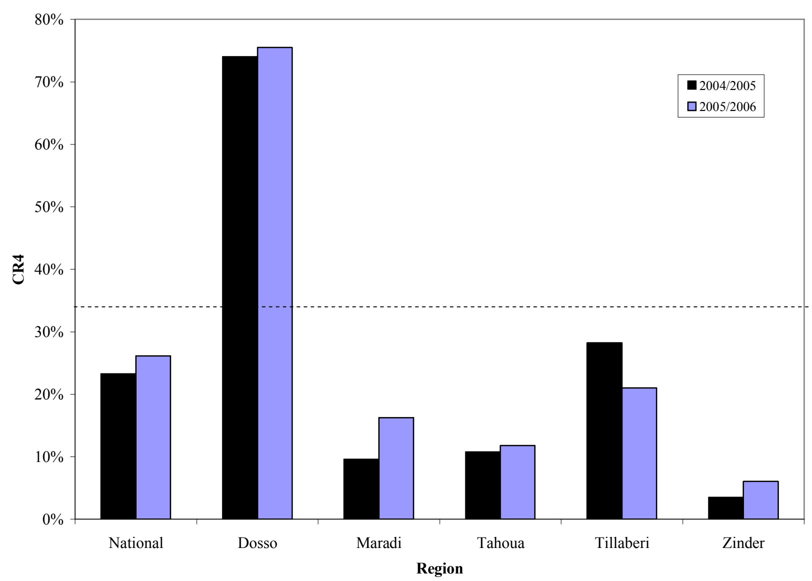
Source: Data collected by the author from the *Société Nigérienne des Télécommunications* (SONITEL) and mobile phone companies in Niger (Celtel, Telecel and Sahelcom).

Figure 3. Changes in Price Dispersion Pre- and Post-Cell Phone Coverage (OLS Coefficients on Event Dummies)



Notes: Based upon the statistical model of Jacobsen, Lalonde and Sullivan (1993), whereby price dispersion is regressed on a series of dummy variables pre and post-cell phone coverage. The estimation equation is the following: $Y_{ij,t} = \sum_{k \geq -m} D_{ijt}^{k}\delta_k + \gamma Z_{ij,t} + \theta_t + u_{ij,t}$ Upper and lower confidence intervals are shown.

Figure 4. Four-Firm Concentration Ratio (CR4) per Market Aggregated by Region, 2004-2006



Notes: Four-firm concentration ratios calculated by the author based upon the 2005/2006 Niger trader census data and survey, with retrospective questions on 2004/2005. The CR4 was calculated for each market in the sample (N=35). The regional CR4 was then obtained by an unweighted average of the market-specific CR4s. Kohls and Uhl (1985) suggest that a CR4 of less than or equal to 33 percent is generally indicative of a competitive market structure, while a concentration ratio of 33 to 50 percent and above 50 percent may indicate a weak and strongly oligopolistic market structures, respectively. Based upon these criteria, markets in Niger appear to be competitive, with the exception of the Dosso region. However, this was primarily due to the non-competitive structure of one market located on the border with Nigeria.