Does Digital Divide or Provide?
The Impact of Cell Phones on Grain Markets in Niger*

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Abstract. Between 2001 and 2006, cell phone service was phased in throughout Niger, providing an alternative and cheaper search technology to grain traders and other market actors. We 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 price and the number of markets over which they search, leading to a reduction in price dispersion across markets. To test the predictions of the theoretical model, we use a unique market and trader dataset from Niger that combines data on prices, transport costs, rainfall and grain production with cell phone access and trader behavior. We first exploit the quasi-experimental nature of cell phone coverage to estimate the impact of the staggered introduction of information technology on market performance. The results provide evidence that cell phones reduce grain price dispersion across markets by a minimum of 6.5 percent and reduce intra-annual price variation by 10 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. We provide empirical evidence in support of specific mechanisms that partially explain the impact of cell phones on market performance. Robustness checks suggest that the results are not driven by selection on unobservables, nor are they solely a result of general equilibrium effects. Calculations of the four-firm concentration index suggest that the grain market structure is competitive, so the observed reductions in price dispersion are not due to greater market collusion. The primary mechanism by which cell phones affect market-level outcomes appears to be a reduction in search costs, as grain traders operating in markets with cell phone coverage search over a greater number of markets and sell in more markets. The results suggest that cell phones improved consumer welfare during Niger's severe food crisis of 2005, perhaps averting an even worse outcome.

Key words: Information, Search Costs, Cell Phones, Food Crisis, Niger.

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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

The importance of information for the effective functioning of markets has been a central concern of economic theory for some time (Jensen 2007). Since Stigler's seminal work on the "Economics of Information" (Stigler 1961), a large body of literature has emerged, in an effort to explain how asymmetric information and costly search can explain equilibrium price dispersion for homogeneous goods. Due to limited or costly information, price dispersion across markets is common in developed and developing countries. The purpose of this paper is to estimate the impact of the introduction of a new search technology on dispersion in grain prices for one of the world's poorest countries, Niger.

The linkages between costly search and market efficiency are important for welfare in Sub-Saharan Africa, and particularly Niger. With a per capita GNP of US$170 and an estimated 63 percent of the population living below the poverty line, Niger is the lowest-ranked country according to the United Nations' Human Development Index (HDI). The majority of the population consists of rural subsistence farmers, who depend upon rainfed agriculture as their main source of income. Grains (primarily millet and sorghum) are dietary staples, accounting for over 75 percent of food consumption (FAO and ICRISAT 1996). These commodities are transported from farmers to consumers through an extensive system of markets that run the length of the country, which is roughly three times the size of California. As grain markets occur only once per week, traders have historically traveled long distances to potential sales markets to obtain information on supply, demand and prices.

In 2005, Niger suffered from a severe but localized food crisis, with grain prices representing more than 27 percent of per capita income. Price dispersion among markets in food crisis regions was 20 percent higher than in non-crisis regions.[2] At the time, only 24 percent of the markets in food crisis regions had cell

[1] Based upon interviews with the author during the Niger trader survey of 2005/2006. The original quotation (from Hausa to French) is the following: *"(Avec le cellulaire), en un temps record, j'ai les informations de toutes sortes sur les marchés proches et lointoins…"*
[2] A supplementary appendix of tables and figures (primarily for results "not shown") is available at https://www.are.berkeley.edu/~aker

phone coverage, as compared to 83 percent of markets in non-crisis regions. This striking pattern suggests a potentially causal relationship between costly search, information asymmetries and price dispersion, one that this paper explores in great detail.

Cell phone service was phased-in throughout Niger between 2001-2006. 75 percent of grain markets had cell phone coverage by 2006, with 29 percent of traders surveyed using cell phones for their commercial operations. In 2006, 89 percent of grain traders reported that they depended upon their personal and professional contacts to obtain relevant market information, primarily by traveling to markets or using telecommunications systems. Given the high search and opportunity costs associated with personal travel, cell phones should be able to reduce traders' marginal search costs, thereby allowing traders to search over a larger number of markets and to obtain market information more quickly. This fact is supported by the grain traders themselves. As a grain trader operating in Zinder noted, *"(With a cell phone), I know the price for US$2, rather than traveling (to the market), which costs US$20."*[3]

To determine how a change in search costs might affect traders' behavior, we construct a sequential search model in which traders search for the optimal price for grain, net transport costs. The model presented here is novel in the economic literature on search theory in two ways. First, our model specifically focuses on search from the trader's (supplier's) perspective, which to our knowledge has not been widely addressed in the search literature.[4] Second, this 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. Our model predicts that grain traders' reservation sales price and expected number of search markets will increase in response to a reduction in search costs. Furthermore, we posit that equilibrium price dispersion will decrease as search costs decrease.

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[3] Based upon interviews with the author during the trader survey of 2005/2006. The original quotation (from Hausa to French) is the following: *"(Avec un cellulaire), je cherche les prix avec une carte de 1.000 CFA au lieu de faire un voyage qui coute 10.000 CFA."*
[4] A notable exception is Jensen's (2007) recent work on the impact of cell phones on the fisheries sector in India, in which a two-market model of supplier (fisherman's) search is presented. The model presented in this paper is significantly different from Jensen's theoretical model.

For our empirical application, we use 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 (millet and sorghum) price data over a ten-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, comprised of 395 traders and 205 farmers located in 35 markets across six geographic regions. Survey respondents provided detailed information on their demographic background and commercial operations during the 2005-2007 grain marketing seasons, with a subset of questions on the 2004/2005 marketing season, the year of the food crisis. In addition, the author collected detailed information on the rollout of cell phone coverage between 2001-2006. While the main limitation of the trader-level dataset is the relatively short time period, the advantages are twofold: first, it is a panel of individuals; and second, it provides important data on traders' behavior and market characteristics that complement the market-level analysis using time series data, thereby allowing us to explore the mechanisms behind the estimated treatment effect of cell phones on market performance.

To empirically test the predictions of the model, we use a two-part empirical strategy. First, we 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) equation with pooled treatment, followed by a period-specific DD model with separate treatments. Our 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 and the multiple time periods allow us 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, we control for selection on observables by combining DD estimation with matching techniques. Finally, recognizing that the treatment effect might not be homogeneous, we allow for treatment effect heterogeneity over space and time.

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 after 75 percent of markets have received coverage. 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. Specifically, one may question the assumptions of no selection on unobservables, the non-existence of general equilibrium impacts, or the failure to control for changing degrees of market power through time. In the second part of the analysis, we 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, we 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), we verify that the results are not solely driven by general equilibrium effects by estimating the impact of cell phones on market pairs that do not interfere with each other. Finally, recognizing that reductions in price dispersion could be due to growing market power, we use the trader census and marketing data to calculate an index of market concentration. These results suggest that grain traders do not collude.

After testing for alternative hypotheses at the market level, we investigate the ways in which traders' behavior changes in response to the introduction of cell phones. We 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 underscores the fact that the primary mechanism by which cell phones affect market efficiency is a reduction in search costs and hence transaction costs.

The reduction in price dispersion suggests that cell phones could lead to higher consumer welfare. The presence of cell phones was associated with 3.5 percent reduction in grain prices in food crisis regions during the year of the food crisis. The lower relative prices in cell phone markets could have served as an income transfer to rural households, allowing them to consume for an additional 5-10 days during the food crisis. Our findings suggest that promoting access to information technology can lead to improved welfare for consumers in Niger, especially when the optimal allocation of resources is most needed.

The remainder of this paper proceeds as follows. Section 2 provides an overview of the grain market in Niger, the role of search 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 provides the main estimation results. Section 6 contains a variety of robustness checks. Section 7 explores the specific mechanisms behind the treatment effects. Section 8 assesses the impact of cell phones on consumer welfare during the food crisis, and Section 9 concludes.

2. Background on Niger

2.1. The Grain Market in Niger

Niger, a landlocked country in West Africa, is one of the poorest countries in the world. 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, who are responsible for moving goods via truck, car or boat; and rural and urban consumers, who purchase the final good.[5] Grains are produced by farmers, who sell their production directly to traders (intermediaries) located in the village. These intermediaries in turn sell directly to larger traders (wholesalers) in local markets. Wholesalers are primarily responsible for inter-regional trade, selling the commodity to other wholesalers, retailers or consumers in regional and national markets. Retailers sell directly to both urban and rural consumers. As there is only one growing season per year (October-November), 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 5 km to over 800km.[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 the 1990s, 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 2007). The average correlation coefficient for prices among grain markets is .56, well below price correlation coefficients computed for other agricultural products in the developing world (Jones 1968, Timmer 1974, Trotter 1991). In addition, grain markets consistently violate the Law of One Price, suggesting that there are persistent unexploited spatial arbitrage opportunities (Aker 2007).

2.2. Cell Phones

Cell phone service first became available in part of Niger in October 2001. Although private cell phone companies (Celtel, SahelCom and Telecel) initially intended to provide universal coverage, due to high

[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 markets for which trade occurred between 2000-2006, based upon the author's survey and secondary sources.

fixed costs and uncertainty about potential customers, cell phone service was introduced gradually. The criteria for introducing cell phone coverage to a market were twofold: first, whether the town was 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 1000km.

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 random spatial pattern of the 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 75 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 by 2006, representing approximately 4 percent of the population (MTC 2006). Nevertheless, cell phones spread quickly among urban residents, functionaries and traders. As of 2006, 29 percent of grains 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$35.

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 consumer search

[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, rather than Chad, Libya and Algeria, due to small population densities along the latter borders.
[8] In Sub-Saharan Africa, only the Democratic Republic of Congo has a lower landline rate per capita, with 1 landline for every 1318 inhabitants.
[9] There were approximately 600 telecenters for the entire country by 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).

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 first approach, known as the "search-theoretic" model, assumes that it is costly for consumers to collect information about prices. Theoretical models in this category include Stigler (1961), Reinganum (1979), MacMinn (1980), Stahl (1989) and Janssen and Moraga-González (2004). A second approach minimizes the role of marginal search costs; rather, it assumes that a subset of consumers can access price information by consulting an "information clearinghouse" (Baye, Morgan and Scholten 2007). Theoretical models outlining this approach include Salop and Stiglitz (1977), Varian (1980), Spulber (1995) and Baye and Morgan (2001).

Most search-theoretic models have been used to explain the existence of price dispersion for homogeneous goods. Nevertheless, the comparative static predictions of these models can be ambiguous. For example, 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 to our knowledge 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 once the minimum price quote is

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[10]Reinganum (1979) develops a model of sequential search and firm cost heterogeneity. A reduction in search costs reduces consumers' reservation price and induces high cost-firms to lower their prices to the reservation price. Since low-cost firms' (monopoly) price is less than consumers' reservation price, price remains unchanged. Thus, a reduction in search costs reduces the range of prices. MacMinn (1980) develops a model of fixed sample search and firm cost heterogeneity. He shows that lower search costs induce consumers to sample more firms, forcing each firm to compete with more rivals. Firms' optimal pricing above marginal cost is reduced, increasing price dispersion (Baye et al, 2007).

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

obtained. Our model 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 a homogeneous good, q (millet in Niger), and a finite number of traders with strictly increasing concave utility functions over income (M), with $u(M) > 0, u'(M) > 0$.[12] Traders know the distribution of prices across all markets at time t, but not the exact market for each price. Prices have a probability density function (pdf) $f(p)$ and a cumulative density function (cdf) $F(p)$ on support $[0, \overline{p}]$. Traders must pay a constant per-km known cost (τ) of transporting the good to the sales market. They engage in sequential search for their optimum price (p), but must pay a constant (per-km) search cost, c.[13]

Suppose that the trader has already searched an arbitrary number of markets, n, and that the optimal (ie, highest) price is z in a market located a distance of k_z. The trader searches an additional time and realizes a price $\hat{p}$ for a market that is k_{n+1} km away. The trader "wins" from this action if the realized price (less transport costs) is greater than the previously optimal prices (less transport costs), and "loses" otherwise. In other words, an additional search is worthwhile if:

$$\hat{p} - \tau k_{n+1} > z - \tau k_z \tag{1}$$

If the trader "wins", his gain in utility is:

$$U_{win}^{gain} = u(\hat{p} - \tau k_{n+1}) - u(z - \tau k_z) \tag{2}$$

And if the trader "loses" the gain in utility is 0, as he or she can simply sell at price z in the previous market:

$$U_{lose}^{gain} = u(z - \tau k_z) - u(z - \tau k_z) \tag{3}$$

We use these expressions to derive the expected benefit function for the *n+1*th search, $B(z)$:

$$B(z) = U(win) * \Pr[win \mid z] + U(lose) * \Pr[lose \mid z] \tag{4}$$

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[12] While traders could simultaneously be buyers and sellers of millet, for simplicity, we assume that traders buy locally and do not search for the best purchase price.

[13] For simplicity, we initially assume that there is a constant per-search cost, *c*, as per-search costs are constant once cell phones are introduced. However, the model and comparative static results can easily be generalized to include a constant per-km cost of search, whereby the total cost of search (via travel) is increasing in distance, k, s.t. $c_{ij} = c * k_{ij}$. This implies that search costs are higher for markets that are farther away.

where $\Pr[win \mid z] = \Pr[\hat{p} > z + \tau(k_{n+1} - k_z)]$ and $\Pr[lose \mid z] = \Pr[\hat{p} < z + \tau(k_{n+1} - k_z)]$. Equation (4) can be rewritten as:

$$B(z) = \int_{z+\tau(k_{n+1}-k_z)}^{\bar{p}} [u(\hat{p} - \tau k_{n+1}) - u(z - \tau k_z)] f(p)dp \tag{5}$$

where $z + \tau(k_{n+1} - k_z)$ is the range of price realizations where the trader wins, $\bar{p}$ is the upper bound of the support, and $B(z) > 0, B'(z) \leq 0$. The expected benefit function is positive but decreasing, implying that the expected benefit from further search is *lower* the higher the current price quote (z).

The trader will weigh the expected benefit with the cost of additional search, defined as his or her net gain function: $h(z) \equiv B(z) - c$. The net gain function defines a decision rule for search: If $h(z) < 0$, the trader will not engage in search; if $h(z) \geq 0$, the trader will engage in additional search to find another price quote that is at or above his or her reservation price, *r*, which solves:

$$h(r) = B(r) - c = 0 \tag{6}$$

Solving for the reservation price allows the trader to identify the "stopping rule". Once the trader realizes a price that satisfies the reservation net gain function defined in equation (6), he or she will no longer search.

Equation (6) can be used to derive partial equilibrium comparative statics for the traders' behavior. Taking the total derivative with respect to r and c yields the following:

$$\frac{dr}{dc} = \frac{1}{u'(r - \tau k_r)[F(r + \tau(k_{r+1} - k_r)) - 1]} \leq 0 \tag{7}$$

This holds since $u'(r - \tau k_r) > 0$ and $F(r + \tau(k_{r+1} - k_r)) \leq 1$. Equation (7) implies that a decrease in search costs will (weakly) increase the traders' reservation price, thus leading him or her to engage in more search, given a particular reservation price.[14]

Although the choice variable in this model is the reservation price, it is also instructive to derive the trader's expected number of search markets. For the n^{th} search, the trader's probability of finding a

[14] A decrease in search costs will unambiguously increase the traders' reservation price if $F(r + \tau(k_{r+1} - k_r)) < 1$

satisfactory price is $\dfrac{1}{1-F(r+\tau k_n)}$. Given independent draws and sampling without replacement, the probability of *n-1* failures followed by success on the n^{th} search is given by $\left(\prod_{i=1}^{n-1} F(r+\tau k_i)\right)(1-F(r+\tau k_n))$.

With the additional assumption of $\tau = 0$, the expected number of searches required to find a price *higher* than the reservation price is $E(n) = \dfrac{1}{(1-F(r))}$.[15] Taking the derivative with respect to *r*, $\dfrac{dE(n)}{dr} > 0$, which implies:

$$\frac{dE(n)}{dc} < 0 \tag{8}$$

In other words, we expect the number of markets over which traders search to *increase* as search costs fall.

These are partial equilibrium results, but we are also interested in general equilibrium predictions. In order to derive them, we need to include potential buyers (consumers) for traders' millet. We assume that there are heterogeneous buyers with downward-sloping demand, located across *n* spatially distinct markets.[16] Following Reinganum (1971) and Baye, Morgan and Scholten (2007), we posit that $\dfrac{d\sigma^2}{dc} > 0$, 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 unit search cost, c, as compared to personal travel. Although cell phones require an initial fixed cost, *F*, for the investment, the variable costs associated with cell phone use are significantly lower than equivalent travel and opportunity costs. For example, in 2006, a two-minute call to a market 65 km away cost US$1, as compared US$2 for roundtrip travel.[17] Cell phones not only decreased traders' travel costs, but also the opportunity costs 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

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[15] We will relax the restrictive assumption of τ=0 in future work. The proof of the distribution function for n-1 failures followed by success, as well as the assumption of independent draws and sampling without replacement, is derived in the online appendix.
[16] Unlike the consumer search models, we do not specify whether buyers are consumers or traders, or the specific source of their heterogeneity. We assume that buyers are heterogeneous *across* markets. Heterogeneity can be thought of as a function of the market's geographic location. This heterogeneity implies that even if buyers have market power – a fact that is not borne out by the data – prices will differ across markets.
[17] Cell phone rates were 160-195 CFA/minute ($ .35-.43/minute) and 35 CFA per text message ($ .07/minute).

agricultural laborer in Niger, the total costs of obtaining information from a market 65km away might have fallen by 50 percent between 2001-2006, the period of large-scale cell phone expansion.[18]

We use the theoretical model to propose the following hypotheses:

- Proposition 1: The introduction of cell phones will lead to an *increase* in traders' reservation price, r, as compared to the traditional search technology, $\frac{dr}{dc} < 0$
- Proposition 2: The introduction of cell phones will lead to an *increase* in the number of markets over which traders search, $\frac{\partial E(n)}{\partial c} < 0$
- Proposition 3: The introduction of cell phones will reduce price dispersion among markets with cell phone coverage, $\frac{d\sigma^2}{dc} > 0$ [19]

The second and third propositions 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, the direction of trade flows and district population levels were also collected.

The second dataset is a unique and detailed panel survey of traders, farmers, transporters and market resource persons collected in Niger by the author between 2005-2007. The survey contains responses of 395 traders located in 35 markets across six geographic regions of Niger. Prior to data collection during the 2005/2006 marketing season, the author developed a census of all grain markets, and markets were randomly sampled based upon the criteria of geographic location, market size and food crisis "status" in 2005. Within each market, we conducted a census of all grain traders operating on the market that day, noting the type of

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[18] 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.

[19] For this prediction, we temporarily appeal to the results found in the consumer search literature with sequential search, heterogeneous agents and downward-sloping demand. The full general equilibrium predictions including consumer demand will be available in later versions.

trader (retailer, intermediary, semi-wholesaler and 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, specifically with respect to the quantities marketed, sales prices, markets and assets.

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, grains traders in Niger trade primarily in agricultural outputs (as opposed to inputs or livestock), 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 search costs, traders' behavior and grain market performance in Niger, we employ a two-part empirical strategy. During the first part of the analysis, we use our time series panel data to estimate the impact of cell phones on changes in the outcome of interest, namely, 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, we 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. Three commonly used measures of price dispersion in the search literature are 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 (less than 15 km), 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 38-750 km. Consequently, the traditional measures of price dispersion are not appropriate for our quasi-experimental setup. Our primary measure of market performance is the price difference between markets *i* and *j* at period *t*, defined as $Y_{ij,t} = | p_{it} - p_{jt} |$. Nevertheless, we use the CV as a robustness check.

To exploit the variation across time and space in the rollout of cell phone towers, we augment the standard difference-in-differences (DD) framework by estimating a double DD specification (Meyer 1995, Bertrand et al 2005).[20] Letting $Y_{ij,t}$ represent the value of the outcome in market pair *ij* at time *t,* we examine the change in $Y_{ij,t}$ before and after the introduction of cell phone towers in each market pair. We first pool the treatments and estimate a multi-period DD equation:

$$Y_{ij,t} = \alpha + \beta_1 evercell_{ij} + \beta_2 cell_{ij,t} + \gamma Z_{ij,t} + a_{ij} + \theta_t + u_{ij,t} \tag{9}$$

where $Y_{ij,t}$ is the absolute value of the price difference of millet between market *i* and market *j* at time *t,* defined as $| p_{it} - p_{jt} |$; $evercell_{ij}$ is a variable equal to 1 if both markets in the pair ever received treatment (a cell phone tower) during the sample period, 0 otherwise; $cell_{ij,t}$ 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.[21] $Z_{ij,t}$ is a vector of exogenous regressors that affect price dispersion, such as transport costs, the presence of drought, gas prices, road

[20] The control structure is twofold: temporal, as we compare treated years (2001-2006) with untreated years (1999-2001); and cross-sectional, as we compare treated markets with untreated markets at time *t*.
[21] The difference between the $evercell_{ij}$ and $cell_{ij,t}$ variables is the following. If market pair *ij* received cell phone coverage in 2004, then $evercell_{ij}$=1 for all *t*, and $cell_{ij}$=1 when t≥2004. If market pair *kl* never received cell phone coverage, then $evercell_{kl}$=0 for all *t*.

quality and the number of traders operating in a market, some of which vary over time. θ_t is a time dummy, either monthly or yearly, and a_{ij} captures unobservable market-pair specific effects.[22] We allow the unobserved effects, a_{ij}, to be correlated with $Z_{ij,t}$ and $cell_{ij,t}$. $u_{ij,t}$ is an error term with zero conditional mean, such 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 (9) can either be estimated via fixed effects transformation or first differencing. 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). As our data are positively serially correlated in levels, we transform equation (9) via first differences to remove the unobserved heterogeneity.[23] This yields the main estimating equation:

$$\Delta Y_{ij,t} = \beta_2 \Delta cell_{ij,t} + \gamma_1 \Delta transport_{ij,t} + \gamma_2 \Delta drought_{ij,t} + \gamma_3 \Delta gas_t + \Delta\theta_t + \Delta u_{ij,t} \tag{10}$$

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. Equation (10) is the primary estimating equation.

We modify equation (10) in a variety of ways. To assess the heterogeneous impact of cell phones across space, we 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*, we include a lagged dependent variable, controlling for joint endogeneity using the Arellano-Bond Generalized Method of Moments (GMM) estimator (Arellano and Bond 1991). These modifications will be discussed in Section 6.

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22 Since *evercell* is time-invariant, it will only be identified if fixed effects are not included, or market pair fixed effects are interacted with time. We do not estimate equation (9) directly, so this equation is only for expositional purposes.

23 Serial correlation in levels is .584(.019). First differencing does not completely eliminate the serial correlation problem, but minimizes the impact. We therefore address 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.

To assess heterogeneous impacts over time, we also modify equation (10) 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. We then exploit the variation in the timing of introduction of mobile phones across market pairs by estimating year-specific regressions. Using the DD framework for each year, we examine the change in outcomes by treatment group between the pre-treatment period (1999-2001) and year *y*, *i.e.* before and after the introduction of cell phones in those market pairs:

$$Y_{ijt,y} = \alpha + \beta_1 cell_{ij,y} + \beta_2 cell_{ij,y} * year_y + \beta_3 year_y + u_{ij,y} \tag{11}$$

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. This empirical implementation includes other exogenous regressors that affect treatment.

A key element for estimating equation (11) is the definition of the treated and untreated market pairs. While treatment status can be defined in a variety of ways, our 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.

Figure 3 demonstrates the identification strategy, showing the relationship between cell phone treatment and price dispersion over time.[24] Grain markets are divided into six categories, with each category defined by the year in which a market pair *ij* first received cell phone coverage. Using the intra-annual CV, we see that price dispersion is initially high during the pre-cell period (1999-2001), with the intra-annual standard deviation of prices approximately 26 percent of the mean price. Once mobile phones are added, this

[24] The intra-annual CV is calculated as the s.d. of grain prices in market *i* over 12 months in year *y*, divided by the mean price of market *i* over 12 months in year *y*.

measure declines dramatically over time; the average CVs of cell phone markets are 9 percent in 2005/2006, with a statistically significant difference between cell phone and non-cell phone markets. The primary deviation from this downward pattern occurs during the 2004/2005 marketing year, when the food crisis was associated with the highest prices on record. While the CVs during this year are relatively higher, they are on average lower than the baseline year. Furthermore, there is a statistically significant difference between cell phone and non-cell phone markets during this year. The fact that the intra-annual CV was large prior to the introduction of cell phones suggests that the net welfare gain is likely to be substantial.

5.2. Dealing with Endogenous Placement of Cell Phone Towers

The fundamental empirical problem that we face in estimating the impact of cell phone coverage is that we cannot observe the outcomes for a treated market pair in the absence of treatment – 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 (Imbens 2004, Rubin 1974, Blattman and Annan 2007). Equations (9)-(11) essentially take this approach. Nevertheless, the estimated ATE will only be unbiased when treatment assignment and the potential outcomes are independent, which is assured with random assignment.

As 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. We are 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 towers. To deal with this concern, we 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.[25] The difference in average price dispersion in the pre-treatment period (1999-2001) was small and not statistically different from zero, at 21 CFA/kg in cell phone markets and 22 CFA/kg in non-cell phone markets. 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, the presence of drought and road quality. The mean differences in drought and road quality are small, and are only significant at the 10 percent level.[26]

A more robust analysis of the potential overlap problem is a comparison of the difference in means with the standard deviation.[27] A difference in average means larger than 0.25 standard deviations is considered to be substantial (Imbens and Wooldridge 2007). Comparing the difference in average means with the standard deviations, we observe that 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.[28] The only exception to this case is the difference in means for urban centers.[29]

Based upon these tests, cell phone and non-cell phone markets appear to differ according to their location in an urban center, the presence of drought and road quality in the pre-treatment period. The relationship between an urban center and cell phone coverage is expected, as a market's probability of receiving cell phone coverage, at least initially, depended upon whether it was located in or near an urban center. Meanwhile, the significance of drought is uncorrelated to treatment assignment.

As cell phone coverage was phased in over time, it is also important to test for potential differences in pre-treatment trends in market outcomes. If trends across treated and untreated groups were the same

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[25] 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.
[26] Border markets are included in the analysis but are not included as a separate category, as they are a subset of urban centers.
[27] 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 (2007) emphasizes that a larger t-statistic for the differences in means does not indicate that the overlap problem is more severe.
[28] 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.
[29] The results are somewhat different when comparing differences in distributions using the Kolmogorov-Smirnov test. In addition to the drought and urban covariates, the differences in distributions for price dispersion and transport costs are statistically significant. Nevertheless, a graphical analysis shows that treated and untreated pairs have similar distributional patterns (not shown).

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 across treatment and control groups is:

$$Y_{ij,t} = \beta_0 + \beta_j pre_j + \sum_{y=1}^{5} \theta_{jy} pre_j * cell_y + u_{ij,t} \tag{12}$$

where $Y_{ij,t}$ is the price dispersion between markets *i* and *j* at time *t*; *pre* is a dummy variable for the change in the pre-treatment periods (1999-2001); and $cell_y$ is equal to 1 if the market pair received cell phone coverage during year *y*, and 0 otherwise. If the θ_{jy}'s are not statistically different from zero, then the pre-intervention trends do not statistically differ among market pairs that received cell phone coverage in different years. The results (Table 3) suggest that pre-intervention trends across market pairs are not statistically different from zero, with the exception of the market pair that received coverage in 2001.[30]

5.3. Estimation under Selection on Observables

To control for potential selection bias, we combine the estimation strategy outlined in equations (9)-(11) with techniques that match treated and untreated market pairs. Results can be sensitive to the estimator chosen, so we use two alternative methods to construct an appropriate counterfactual. In the first method, we include a parametric estimation of the propensity score as an additional control in the DD equations. Under the conditional independence assumption, we can calculate consistent ordinary least squares (OLS) estimates of the treatment effect. A more efficient and consistent approach, however, is a weighted least squares (WLS) regression (Hirano et al 2003, Blattman and Annan 2007). In this case, we first weight the observations by a parametric estimate of the propensity score, where the weights used are the following:

$$\lambda_{ij} = \sqrt{\frac{cell_{ij,t}}{\hat{p}(X_{ij,0})} + \frac{1-cell_{ij,t}}{1-\hat{p}(X_{ij,0})}} \tag{13}$$

[30] We later drop this observation from our estimations as a robustness check below.

The WLS representation allows us to add covariates to the regression function to improve precision. 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 2001). [31]

6. The Impact of Cell Phones on Market Performance

6.1. Average Treatment Effects

Before turning to the regression specification with separate treatment effects, we first pool the treatments and estimate equation (10). Table 4 presents the regression results of the DD model using a first-differenced transformation, controlling for exogenous regressors, market-pair fixed effects and time dummies.[32] Column 1 shows that cell phones are associated with a negative (-4.6 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. [33] Transport costs and gas prices are associated with higher price dispersion between markets, although neither coefficient is statistically significant. Since first-differencing removes a large degree of cross-sectional variation, this is not surprising. However, it could suggest that grain price dispersion is not highly elastic to changes in gas prices. The presence of drought in a particular year is associated with a statistically significant increase in price dispersion across markets.[34] Column 2 uses an alternative measure of market performance, the intra-annual CV for market *i*. Cell phone towers are associated with a .024 and statistically significant reduction in the CV, implying that the intra-annual price dispersion is 10 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.

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), also known as the random trend model (Wooldridge

[31] This approach controls for selection on the observables, and is an efficient estimator of the ATE if we assume homogeneous treatment effects, and an efficient estimator of the average treatment effect on the treated (ATT) if there are heterogeneous treatment effects. While using the weighted propensity score is more efficient, it is also sensitive to a misspecification, which can result in additional bias.

[32] For all specifications, the Law of One Price was also used. The coefficients were nearly identical, and so these results are not reported.

[33] The %Δ is calculated as the treatment effect relative to the mean price dispersion for non-cell phone markets in the pre-treatment period.

[34] *Drought dummy*=1 if rainfall in a particular market is two standard deviations below the average rainfall for that market during the rainy season, and/or the lack of rainfall for more than 15 consecutive days.

2002). Including the trend increases the point estimates slightly, but does not affect the standard errors. In Column 5, we control for 84 monthly time dummies, as opposed to yearly time dummies, as well as the market pair time trends.[35] The coefficient estimate for cell phone decreases dramatically, from 4.55 to 1.42, and is marginally statistically significant. This is not surprising, as the treatment assignment is monthly, and monthly time dummies 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 this conservative estimate of -1.42 CFA/kg, cell phone coverage is associated with a 6.4 percent reduction in price dispersion as compared to untreated market pairs.

Until now, a key assumption of our 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, as is the case if $Z_{ij,t}$ contains a lagged dependent variable. However, it is reasonable to assume that grain market performance does not adjust instantaneously, and depends upon market performance in a previous period. We therefore modify equation (10) to include a lagged dependent variable:

$$\Delta Y_{ij,t} = \rho \Delta Y_{ij,t-1} + \beta_2 \Delta cell_{ij,t} + \gamma_1 \Delta transport_{ij,t} + \gamma_2 \Delta drought_{ij,t} + \Delta gas_t + \Delta \theta_t + \Delta u_{ij,t} \qquad (14)$$

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, we control for endogeneity by using the Arellano-Bond GMM estimator (Arellano and Bond, 1991).[36] This is equivalent to the first-differenced DD regression with market-pair trends presented in Columns 3 and 5.

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, gas prices and time dummies, the

[35] As the CV is calculated on a yearly basis, monthly time dummies are not included for these regressions.

[36] After first-differencing, the lagged-dependent variable is correlated with the composite error term through the contemporaneous terms in period $t - \tau$. Hence, instrumental variables are required. We therefore use the past values of the explanatory variables as instruments for the lagged dependent variable in a GMM framework (Arellano and Bond, 1991). The consistency of the estimator depends upon the assumption that the lagged variables and other explanatory variables are valid instruments. A necessary condition in this respect is the lack of τ -order serial correlation in the error terms after first-differencing. We conduct the Sargan test of overidentifying restrictions and test for no serial correlation in the errors. The z-statistic of the Sargan test is -.15, so we cannot reject the null hypothesis of no autocorrelation of order 2 in the residuals.

coefficient on the lagged dependent variable is negative and statistically significant in both models, implying that it takes 2.5 months for price differences across markets to adjust.[37] The coefficient on cell phones is still negative and statistically significant at the 10 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 $\frac{\beta_2}{1-\rho}$. Using this formula, cell phones are associated with a 2.5 CFA/kg reduction in price dispersion in the long-term, and this effect is strongly statistically significant. However, the magnitude and statistical significance drop when monthly time dummies are included. This is not surprising, as double-differencing and monthly time dummies account for most of the cross-sectional and temporal variation in treatment.

6.2. Heterogeneous Treatment Effects

By pooling the treatments, we are measuring the average impact of cell phones on price dispersion, thereby assuming a homogenous treatment effect. We can also examine how the impact of cell phones varies across time and space. To identify treatment effect heterogeneity across space, we interact the cell phone treatment with gas prices, distance and road quality. The regression results for these interactions are provided in Table 5. The coefficient on the interaction term between cell phones and gas prices is marginally positive yet not statistically significant (Column 1). The joint effect of cell phones and gas prices is -4.5 CFA/kg and strongly statistically significant, suggesting that cell phones are associated with a 20 percent reduction in price dispersion. Once monthly time dummies and market-pair time trends are included (Column 2), the interaction term remains positive, whereas the magnitude of the cell phone coefficient decreases to -2 CFA/kg. Overall, the joint effect of cell phone coverage is negative and statistically significant at the 5 percent level.

[37] The coefficient on the lagged dependent variable can be interpreted as the speed of adjustment. As the Arellano-Bond regression is run in first differences, the regression is second-differenced. This explains why the coefficient on the lagged dependent variable is negative. We use the concept of a "half-life" to interpret the results, calculated as $\ln(.5)/\ln(1+\rho)$.

To determine how the impact of cell phone differs across space, we 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 6.7 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, we split the sample into short haul (less than 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. 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.[38] The results are similar when interacting cell phones with road quality (Column 8). Cell phones have a stronger impact on price dispersion for markets with unpaved roads, and the joint effect is statistically significant at the 1 percent level. Splitting the sample between paved and unpaved roads (Columns 9 and 10), cell phones are associated with a -3.6 CFA/kg reduction in price dispersion for markets with unpaved roads. A Chow test for the joint significance of the split sample is F(11, 432)=5.34, allowing us to reject the hypothesis that there is not a statistically significant difference between the samples.

As cell phone towers were gradually 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 coverage. To identify treatment effect heterogeneity over time, we interact the cell phone dummy with a variable that

[38] A Chow test for the joint significance of the split sample reveals that the difference among the three samples is statistically significant from zero. Regressing price dispersion on cell phones and distance reveals that there is a quadratic (inverted U-shape) 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 greater than 589 km apart.

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 6. The interaction term between cell phones and the cell phone network is strongly negative (-12 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. Specifically, when 14 percent of market pairs had cell phone coverage in 2003, price dispersion was 1.6 CFA/kg lower in cell phone market pairs. When over 75 percent of market pairs had cell phone coverage in 2006, price dispersion was 8 CFA/kg lower in cell phone markets. 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 1.8 CFA/kg reduction in price dispersion. This result is similar when using the CV (Column 2), suggesting that cell phone markets are associated with a .05 reduction in intra-annual price dispersion. Such findings are intuitive: cell phones are more likely to be useful to traders as network coverage increases, since traders are then 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. By regressing price dispersion on a quadratic of the network variable, we find that there is a nonlinear relationship between network coverage and price dispersion. This suggests that there could be diminishing marginal effects of cell phones on price dispersion after 75 percent of markets have cell phone coverage. We investigate this nonlinear relationship using two techniques. First, based upon the "event study" approach outlined in Jacobson et al (1993), we introduce a series of dummy variables for the number of months before or after a market pair receives cell phone coverage. Accordingly, we let $D_{ijt}^{k}=1$ 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, we 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.[39]

Figure 4 graphs the coefficients on the dummy variables pre- and post-cell phones, controlling for time-varying covariates and a year time trend. We fail to reject the hypothesis that the dummy variables prior to cell phone coverage are zero, but we strongly reject the hypothesis that the dummy variables are equal to zero post-treatment.[40] Consistent with the regression results, we find that cell phone markets have lower price dispersions. This reduction is strongest in the initial 4 months' after coverage, with an average of -5 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 6 months' after coverage. Because the estimated reduction in price dispersion does not decline significantly 10 months' after coverage (the coefficient is -3.5 and statistically significant at the 5 percent level), there is little evidence that cell phone markets will return to their pre-treatment price dispersion levels (not shown).[41]

A more conventional way of testing for a heterogeneous average treatment effect is to run period-specific DD estimations, as outlined in equation (11). Table 7 shows the results of these regressions using a varying treatment group and constant control group in each year. Similar to the pooled DD regressions, we compared the differences in means and distributions of the pre-treatment covariates by treatment group. These comparisons show that we cannot reject the equality of means for all pre-treatment covariates for most years, with the exception of the "urban center" variable (not shown).[42]

Overall, the results in Table 7 are consistent with the pooled regressions. In the initial years of cell phone coverage (Panels A-B), the impact of cell phones on price dispersion is not statistically significant.

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[39]More formally, the estimation equation is the following:

$$\Delta Y_{ij,t} = \sum_{k \geq -m} \Delta D_{ijt}^{k} \delta_k + \gamma_1 \Delta transport_{ij,t} + \gamma_2 \Delta drought_{ij,t} + \gamma_3 \Delta gas_t + \Delta\theta_t + \Delta u_{ij,t}$$

[40] The F-statistic for pre-treatment dummies is F(5, 299)=.93, so we fail to reject that the dummies are jointly equal to zero. The F-statistic for the post-treatment dummies is F(6,299)=7.11, so we strongly reject the joint hypothesis that the post-treatment dummies are equal to zero. Each of the individual post-treatment coefficients is strongly statistically significant. Extending the timeline to 10 months' pre and post-treatment yields similar results post-treatment, but we can no longer strongly reject that the pre-cell coefficients are equal to zero.

[41] Using an alternative approach yields similar insights the nonlinear effect of cell phones on price dispersion. Following the approach outlined in Brown and Goolsbee (2002), we find that price dispersion falls as the share of markets with cell phone coverage is between 20 and 75 percent.

[42] Treatment and control groups were also identified using alternative specifications, but the regression is not reported, as the results are similar.

This coincides with the periods when approximately 14 percent of markets had cell phone coverage. In 2003/2004, cell phones are associated with a reduction in price dispersion (Panel C), but this effect is not statistically significant. It is not until 2004/2005, when approximately 55 percent of markets have cell phone coverage, that cell phones are associated with a negative and statistically significant reduction in price dispersion (Panel D). By the final year, the impact is still negative but no longer statistically significant. This supports the previous results concerning network externalities, suggesting that a "critical mass" of the cell phone network might have occurred in 2004/2005. When 75 percent of markets have cell phone coverage (2005/2006), there are diminishing marginal effects of cell phones on price dispersion.

6.3. Controlling for Selection Bias

In an effort to consistently estimate the treatment effect of cell phones on market performance, we control for potential selection on observables by combining the DD estimation strategy with matching. We first estimate the propensity score parametrically by estimating a probit regression of the treatment (cell phone towers in a market pair) on pre-treatment covariates, including variables that simultaneously influence the treatment decision and the outcome variable (Smith and Todd 2005, Sianesi 2004).[43] To provide empirical evidence that the propensity score matching approach is reasonable, we inspect the Box-Plots and histograms of the estimated propensity scores by treatment group. Figure 5 shows that there is considerable overlap in the propensity scores of cell phone and non-cell phone market pairs. In addition, a comparison of the differences in means and distributions of the matched samples shows that the equality of means and distributions cannot be rejected for most of the pre-treatment covariates (not shown).

Table 8 shows the results of pooled DD regression, correcting for selection on observables using WLS and the propensity score as an additional control.[44] The results are consistent with the unmatched

[43] There is little advice available regarding which functional form to use for estimating propensity scores. We used a parsimonious probit to estimate the propensity score, including transport costs, distance, drought, road quality, market size, urban center and interaction terms between transport costs, road and drought (not shown).

[44] 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. While bootstrapping is popular in the program evaluation literature, Imbens (2004) notes that there is little formal

samples, although the magnitude and significance of the impact of cell phones is stronger for all specifications, even when controls for the 84 monthly time dummies and group-specific trends are included. Cell phones are associated with a -5.7 CFA/kg reduction in price dispersion for all models controlling for yearly time dummies and market-pair trends (Columns 1-2), and are strongly statistically significant, implying that price dispersion in cell phone market pairs is 26 lower than non-cell phone markets. Once monthly time dummies are included (Columns 3-4), the magnitude of the coefficient drops significantly, but the effect is still negative and statistically significant; cell phones are associated with a 1.8-2.7 CFA/kg reduction in price dispersion. Adding an interaction term between cell phones and network coverage yields similar results to the unmatched regressions (Columns 5-6). The joint effect of cell phones and network coverage is negative and statistically significant, confirming that the effect of cell phones is stronger as the network expands.

The period-specific DD regressions controlling for selection bias support the unmatched results (not shown). Cell phones are associated with a statistically insignificant impact upon price dispersion between 2001-2003, when less than 30 percent of markets had cell phone coverage. By 2004/2005, cell phones are associated with a 3.5-3.9CFA/kg and statistically significant reduction in price dispersion across markets. The negative impact of cell phones on price dispersion continues until 2005/2006, although the magnitude decreases slightly to -2.8 CFA/kg. Nevertheless, the effect is statistically significant at the 5 percent level for both the WLS and propensity score estimates.

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 selection on observables and the non-existence of general equilibrium impacts. In addition, excess price dispersion could arise for other reasons, such as an uncompetitive market structure, high transactions costs or credit market failures.[45] We next provide

evidence to justify the approach. Standard errors presented in Table 8 are clustered by market pair-month, but bootstrapping was also used, with similar results.

[45] In related research, we show that markets are integrated, with transaction costs representing approximately 15 percent of the final sales price (Aker 2007). The trader-level survey also suggests that credit constraints could be a concern for traders in Niger. This implies that lower search

empirical evidence in support of specific mechanisms that partially explain the impact of cell phones on market performance. We first explore alternative explanations of our results before investigating the ways in which traders' behavior changes in response to the introduction of cell phones.

7.1. Selection on Unobservables

An important concern with the previous estimates is the potential for unobserved selection and bias. Several plausible sources of bias exist, such as political pressures affecting cell phone companies' selection of cell phone markets or broader economic factors that simultaneously affect market performance and the timing of cell phone rollout.

The conditional independence assumption (CIA) used throughout this paper is not directly testable.[46] Nevertheless, there are indirect ways of assessing this, a number of which are developed in Rosenbaum (1987), Heckman and Hotz (1989) and Imbens (2003). These methods can be divided into two broad groups. The first set of tests focus on conducting a series of robustness checks by estimating a causal effect that is known to equal zero. The most common approach estimates the treatment effect on a variable known to be unaffected by it, typically one whose value is determined prior to the treatment (Imbens and Wooldridge 2007). If the estimated treatment effect is close to zero, it is more plausible that the CIA holds. A second series of tests, known as sensitivity analysis, explicitly relax the CIA (Imbens 2003, Blattman and Annan 2007). This paper focuses on the first set of tests.

In order to assess conditional independence, we estimate the impact of cell phones on price dispersion between 1999-2001. This is prior to the introduction of cell phones in October 2001, so the outcome variable cannot be affected by the treatment (Imbens and Wooldridge 2007). For all six tests of violations of the CIA (Table 9), the estimated effect is close to zero and not statistically significant at

costs would not necessarily lead to more arbitrage unless they simultaneously addressed the credit market failures. We do not address credit constraints in this paper, but we posit that the reductions in price dispersion presented here are a lower bound.

[46] The CIA states that the conditional distribution of the outcome under the control treatment is identical to the distribution of the control outcome. The same is assumed for the distribution of the active treatment outcome. However, since the data are uninformative about the distribution of the unobserved counterfactuals, we cannot use the data to directly reject the CIA.

conventional levels. The results suggest that conditional independence is plausible, and that selection on unobservables is not an overwhelming concern.[47]

7.2. General Equilibrium Effects

Until now, we 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). Either case would violate the stable unit treatment value assumption (SUTVA).[48] In this context, standard policy evaluation practices can either under- or overestimate the treatment effect.

The econometric literature on program evaluation assumes no interactions among the agents being analyzed, and often ignores the market consequences of treatment effects (Heckman, Lockner and Taber 1998). Consequently, there is little guidance for evaluating treatment effects in a general equilibrium setting (Rosenbaum 1987). A common approach is to combine smaller treatment units into larger units that do not interfere with one another. We use this approach in an attempt to address the potential "downstream" general equilibrium impacts on the treatment effect.[49]

We first identify two remote regions of Niger, Zinder and Tillaberi, which are more than 750 km apart and have different trade patterns. Zinder is Hausa-speaking region located in the far east of the country, considered to be one of the "breadbaskets" of Niger. Markets located in Zinder trade primarily

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[47] We also regressed price dispersion on observed covariates. The correlation between these predicted values and treatment assignment is -.01, further supporting our argument that unobserved bias is of little concern.

[48] Rosenbaum (1987) identifies two potential violations of SUTVA: "interference between units", whereby the treatment assignment of one unit affects other units; and "intervening treatments", whereby treatment is applied after the primary treatment. In our case, the potential violation of SUTVA relates to the former example.

[49] We would be concerned about "upstream" equilibrium effects if farmers' grain production was elastic and cell phones had an impact upon farm-gate prices. We feel as if these are not overwhelming concerns for two reasons. First, most grains are purchased from farmers directly in the village. By 2007, only 5 percent of villages had cell phone coverage. Second, based upon the Niger farmer survey conducted by the author, less than 14 percent of farmers surveyed stated that they considered farm-gate prices when making production decisions. This suggests that the production system for grains is fairly rigid, and hence upstream general equilibrium effects should not be a primary concern.

with Nigeria and the eastern regions of the country. Tillaberi is a Zharma-speaking region located to the far west of the country, with relatively low levels of per capita agricultural production. Markets in the Tillaberi region trade primarily with Burkina Faso and Mali. Trade did not occur between Zinder and Tillaberi between 2000-2006, suggesting that market pairs within these regions do not interfere with each other. Finally, none of the markets in either region received cell phone coverage until 2003.

To assess the impact of the introduction of cell phones, we first identify treated and control units (market pairs) *within* each region which are not linked by trade. Each region has distinct trade flow patterns, which allow us to identify intra-regional market pairs that do not interfere with one another.[50] Once these treated and control groups are identified, we match cell phone market pairs *within* Tillaberi to non-cell phone market pairs *within* Zinder, and vice versa. We then use these matched pairs to estimate the DD regression with pooled treatments, controlling for observable characteristics.[51]

In comparing the differences in means of pre-treatment covariates by cell phone market and region, none of the inter-regional differences in means are statistically different from zero (not shown). The only exception is market size, as non-cell phone markets in Zinder have, on average, a larger number of traders than the treated markets in Tillaberi. This suggests that selection on observables is not an overwhelming concern, although we control for potential selection bias.

Table 10 presents the results of the DD regressions. Overall, the magnitude and statistical significance of the coefficients 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 at the 1 percent level (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 general equilibrium effects in previous analyses could have underestimated the treatment effect.

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[50] Intra-regional trade flows are based upon data collected by the author and from secondary sources. Markets within Tillaberi trade according to their location north or south of the Niger River. Trade flows within Zinder are dominated primarily by markets' proximity to Nigeria.
[51] We also matched "non-interfering" treated and control pairs within each region, yielding negative and statistically significant treatment effects.

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

7.3. Market Power

A final potential concern in assessing the impact of cell phone technology on price dispersion is the question of market power, or the number and relative size distribution of buyers and sellers in a market. If the grain market structure is oligopolistic, then a reduction in price dispersion may simply be an indication of convergence towards the "monopoly" price, rather than a reduction in transaction costs.

The existing literature suggests a number of measures of market power. The most commonly used is the market concentration index, which measures the percentage of traded volume accounted for by a given number of participants. Such measures are often used as "rules of thumb", as there may be reasons why high concentration levels may be reasonable in light of small potential volumes traded.[52] Notwithstanding these caveats, we use the trader survey data to calculate the four-firm concentration ratios (CR4s) for the 2004/2005 and 2005/2006 marketing seasons. Overall, the CR4s suggest that the grain market structure is fairly competitive (Figure 6).[53] Nationally, the largest traders accounted for 23 percent of grain traded in 2005/2006, and 13 percent of all grain traded in 2004/2005, the year of the food crisis. Markets appear to be fairly competitive across regions as well, with most regions having a CR4 less than 25 percent. These results provide evidence that reductions in price dispersion are not driven by convergence to a monopoly price.

7.4. Cell Phone Towers and Traders' Behavior

[52] In addition, it is important to note that farmers in Niger buy and sell a large percentage of their cereals via intermediaries, bypassing the grain wholesalers who are the focus of market concentration analyses.
[53] 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 33-50 percent and above 50 percent may indicate a weak and strongly oligopolistic market structures, respectively.

The theoretical framework of sequential search derived some partial equilibrium predictions for traders' behavior in response to a change in search costs. Until now, we have assumed that reductions in price dispersion are driven by changes in traders' search behavior. An investigation of alternative explanations appears to support these results, but we need to test this empirically using the trader-level data.

In order to measure the impact of cell phones on traders' behavior, we estimate an equation analogous to equation (11):

$$Y_{ij,t} = \alpha + \beta_1 cell_{j,t} + \delta X_{ij,t} + \gamma Z_{j,t} + \theta_t + u_{ij,t} \tag{16}$$

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 consulted for 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 the market has mobile phone access, and 0 otherwise. $X_{ij,t}$ 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, level of education and type; $Z_{j,t}$ is vector of exogenous pre-treatment regressors of market *j* at time *t*, including the number of traders operating in the market, the presence of 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 the identification of β_1 principally relies upon the quasi-experimental nature of the rollout of cell phones across markets and over time.[54]

All of the outcome variables in equation (16) are either binary or non-negative count variables that take on relatively few values. For binary dependent variables, we use probit maximum likelihood estimation.

[54] Equation 16 defines treatment as the presence of a cell phone tower in market *j* at time *t*, rather than the traders' cell phone adoption decision.

For the count variables, we use Poisson maximum likelihood estimation.[55] However, we also provide the OLS estimates for comparison.[56]

Similar to the market-level identification strategy, the fundamental empirical problem that we face is that we cannot observe a trader's outcomes had or she not received treatment. In particular, we are 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.

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

Furthermore, traders' "self-selection" into cell phone markets does not seem likely. Based upon the trader censuses conducted between 2004-2007, the number of traders per market did not vary significantly on an inter-annual basis.[57] This coincides with the period of significant expansion in cell phone coverage, and one during which we 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 market" since they began trading. 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 home 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 actually relocated to a market *without* a cell phone tower.

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[55] If the assumption of a Poisson distribution is not valid, the analysis is a quasi-maximum likelihood estimation (QMLE). We will still get consistent and asymptotically normal estimators whether the Poisson distribution holds. However, if the Poisson variance assumption does not hold, then we need to adjust the Poisson MLE standard errors.
[56] Although we cannot directly compare the magnitude of the Poisson estimates with the OLS estimates, we can provide a rough comparison.
[57] A census of traders on each market was conducted during the 2005/2006 and 2006/2007 marketing seasons. Data on the number of traders on each market in 2004/2005 was retrospective, collected during the author's interviews with market resource persons.

The trader survey data appear to support these claims. Table 11 presents the differences in means and distributions of pre-treatment covariates for traders located in cell phone and non-cell phone markets.[58] Surprisingly, none of the differences in means for trader-level covariates are statistically different from zero, with the exception of having a bank account (Panel A). The results are similar using an alternative definition of the pre-treatment year. In looking at market-level covariates (Panel B), we 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 urban center.[59] Overall, these results suggest that selection on observables is not an overwhelming concern.

Controlling for pre-treatment trader and market-level characteristics, the effect of cell phone towers on traders' behavior appears to be substantial. Table 12 presents the regression results of equation (16) using OLS (Column 1), Poisson (Column 2), probit (Column 3) and propensity score matching (Column 4). Based on the OLS estimates, 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. This confirms our theoretical prediction that a reduction in search costs would lead 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. Similarly, the Poisson coefficient suggests that the expected number of people that traders' consult is 33 percent higher in cell phone markets. 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, although the marginal effect is stronger.

[58] The "correct" definition of the pre-treatment year is 2001, prior to the date when any of the markets were treated. However, our trader-level data is only from 2004. To address this issue, we 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, we 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. We posit that changes in most of the relevant time-variant covariates between 2003-2004 are highly unlikely.

[59] As data on market-level covariates are available from 1999, the comparisons for market-level covariates are for 1999-2001.

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 estimates are only statistically significant for the probit regression. Finally, 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. The magnitude of this difference is easier to understand once we consider that grain traders in non-cell markets only trade in an average of 4 markets per year. Therefore, one market represents a 25 percent increase in traders' sales markets. 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 3).[60]

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, on the other hand, 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, we can either explicitly model the process determining selection (Heckman 1979), or construct bounds of the treatment effect (Manski 1990, Rosenbaum 2002, Lee 2005). We adopt the latter approach, whereby upper and lower bounds for differential selection are calculated by trimming the distribution (Lee 2005, Blattman and Annan 2007).[61] We first construct the "best-case" bound by dropping traders in cell phone markets who have changed their principal market and

[60] Future research will also investigate the effect of cell phone towers on traders' sales' prices, as initial evidence suggests that cell phone towers are associated with an increase in the price that traders' receive during the hungry period.
[61] Lee's method is specifically used for selective attrition, and was applied in Blattman and Annan (2007). Rosenbaum (2002) specifically outlines an approach for testing the sensitivity of the average treatment effect with respect to changes in unobserved characteristics.

then calculating the 'trimmed' treatment effect. The "worst-case" bound is calculated by dropping traders in non-cell phone markets who have changed their principal market.[62]

Bounds for each outcome are provided in Table 13. 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. These results are quite strong, since none of lower bounds changes sign and many of them are still statistically significant. The results imply that even under strong trader selection, cell phone towers still have a statistically significant effect on traders' behavior.

8. Cell Phone Coverage and Consumer Welfare during the 2005 Food Crisis

The previous results suggest that there are potential welfare improvements associated with the introduction of cell phones in Niger. Nevertheless, it is difficult to determine how this welfare gain is distributed among farmers, traders and consumers (Jensen 2007). To provide a simple estimate of consumer welfare, we assess the impact of cell phones on consumer grain prices during the 2005 food crisis. We hope to extend this analysis in future work by estimating the welfare impacts of cell phones on traders' and farmers' profits.

In 2004/2005, Niger experienced a severe drought and food crisis, with grain prices the highest on record. Grain prices per 100-kg sack were 8 percent higher in food crisis regions as compared to non-crisis regions, and represented approximately 27 percent of per capita income. Over 83 of markets in non-crisis regions had cell phone towers, as compared with 20 percent of markets in food crisis regions. This suggests a potential correlation between asymmetric information, search costs and the crisis.

In order to consistently estimate the effect of cell phones on consumer welfare, we need to find suitable treated and untreated groups for comparison. Unlike our previous approach, we will not match on

[62] Blattman and Annan (2007) used a similar approach to deal with selective attrition, calculating upper and lower bounds and for the ATE of child abduction.

pre-treatment covariates, but rather compare cell phone and non-cell phone markets during the year of the food crisis. The relevant question is therefore whether, for given market conditions in 2004/2005, cell phone access was associated with higher (or lower) consumer prices.

Recognizing that there could be unobserved differences among food crisis and non-crisis regions, we focus on the impact of cell phones *within* food crisis regions, as presumably markets within the same regions would have fewer differences in observed and unobserved heterogeneity. A comparison of observables confirms this assumption (not shown). Using pooled DD estimations for the year of the food crisis (Table 14), the results suggest that, on average, cell phones were associated with a -7.5 CFA/kg reduction in consumer grain prices. As the mean grain price in untreated markets was 212 CFA/kg during the crisis year, this implies that grain prices in cell phone markets were 3.5 percent lower. The effect of cell phones on the intra-annual CV during the food crisis is also negative, but not statistically significant at conventional levels.

While we do not have the data to undertake a full welfare analysis, we provide a rough approximation. We 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 who pays a price of p per unit of millet and has an income of M is $V(p,M)=v(p)+M$, where $V(p,M)$ is non-increasing in p.[63]

Prior to the introduction of cell phones in a particular market, consumers face an intra-annual distribution of millet prices, $F(p) \sim p_F, \sigma_F^2$. After the introduction of cell phones, consumers face a distribution of $G(p) \sim p_G, \sigma_G^2$, where $p_F > p_G, \sigma_F^2 > \sigma_G^2$. A graphical analysis of the density functions of grain prices by cell phone coverage during the year of the food crisis supports these assumptions (not shown). This suggests that $\int_0^{\bar{p}} G(p)dp \le \int_0^{\bar{p}} F(p)dp \forall p \in [0,\infty]$, implying that $G(p)$ second-order stochastically dominates $F(p)$. Consequently, risk-averse, expected utility-maximizing consumers would prefer $G(p)$.

[63] Wright and Williams (1988) provide a framework for analyzing the welfare effects of price stabilization. We cannot adopt this framework here, but we hope to use forthcoming World Bank data on Niger to estimate a consumer demand curves and construct measures of consumer welfare.

Lower relative grain prices in cell phone markets suggest that consumers would have been able to increase consumption during the food crisis. As households in Niger consume a minimum of 225 kg of millet over a three-month period, lower grain prices would have served as an income transfer to rural households. All else equal, households in cell phone markets (in the food crisis regions) were able to purchase an additional 13.5 kg of grain during the food crisis, equivalent to 5-10 days' worth of millet consumption. While this magnitude seems small, children can become severely malnourished (due to reduced caloric consumption) within a 7-day period (MSF 2005). Consequently, the additional consumption could have reduced the severity of the food crisis.

9. Conclusions

In this paper we provide some estimates of the nature, magnitude and distribution of the effects of cell phones on grain market performance, traders' behavior and consumer welfare in Niger. The introduction of cell phones reduced price dispersion across grain markets, with a statistically significant reduction in price levels during the year of the food crisis. These results provide empirical evidence of the importance of information for market performance.

These findings can be juxtaposed against current development priorities for international, governmental and non-governmental organizations. Information technology is often considered to be a low priority when compared to other basic needs, such as food, water, shelter and health care (Jensen 2007). While basic needs cannot or should not be overlooked, cell phones could be a powerful development tool for farmers, traders and consumers. Information technology can not only increase poor households' purchasing power (via lower consumer prices) but also incomes, as farmers search for the optimal price for their goods. In addition, traders appear willing to adopt the cell phones, suggesting that the technology could be sustainable. This point is important for the current debate concerning the relevance of agricultural extension and market information systems as a development tool in Sub-Saharan Africa. Providing information is not enough; it must be symmetric, complete, appropriate and timely in order to be used. Cell phones could help to meet these needs.

In order to generalize these results beyond Niger, some final words of interpretation on the treatment effects are necessary. Although cell phone coverage is associated with a reduction in price dispersion, the fact that our counterfactual is possibly affected by cell phone coverage in other markets suggests a potential source of bias that we cannot address. For instance, cell phone coverage appears to affect traders' behavior, and could reduce the quantity of grains supplied to non-cell phone markets. Although we attempted to estimate the treatment effect in light of SUTVA violations, there is still the possibility that our treatment effect might overestimate the impact of cell phone coverage in Niger.

Finally, while our results suggest there have been welfare gains associated with the introduction of cell phones in Niger, we have not undertaken a full welfare analysis. Consequently, we do not know whether these changes are Pareto-improving. While initial analyses suggest that traders in cell phone markets receive higher prices, we will extend this analysis in future work by estimating the impact of cell phones on traders' profits in order to better understand how welfare gains are distributed.

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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	0.19	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
Types of income-generating activities		395
Farmer	0.84	319
Herder	0.05	20
Private or public sector employee	0.01	2
Chauffeur	0.01	3
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. All prices are in 2001 CFA.

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

Pre-Treatment Observables	Unconditional Mean: Cell Phone Mean (s.d.)	Cell Phone Obs	No Cell Phone Mean (s.d.)	No Cell Phone Obs	Difference in Means: Unconditional s.e.	Difference in Distributions: Unconditional Kolmogorov-Smirnov Test D-statistic	p-value
Panel A. Market Pair Level Data							
Price dispersion between markets (CFA/kg)	20.72 (16.8)	7392	22.14 (16.46)	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)	0.075	0.768
Road Quality between markets	0.418 (.493)	10296	.318 (.465)	2640	.100*(.052)	0.1	0.331
Market Size	1.47 (1.88)	10296	1.85 (1.99)	2640	-.377(.217)	0.113	0.245
Drought in 1999 or 2000	.043 (.203)	10296	0.077 (.267)	2640	-0.034* (.018)	0.034*	0.024
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)	12.7 (6.89)	10296	12.7 (7.12)	2640	0.013 (.771)	0.052***	0
Panel B. Market Level Data							
Price level (CFA/kg)	128(34.18)	1801	115.22(35.3)	196	12.84(8.13)	0.375***	0
Road Quality to Market	0.629(.483)	1944	.5(.5)	288	.129(.271)	0.129	0.12
Market Size	103.11(79.61)	1944	101.75(45.3)	288	1.361(27.79)	0.379***	0
Drought in 1999 or 2000	0.296(.457)	1944	0.5(.505)	288	-.203(.270)	0.203*	0.062
Urban center(>=35,000)	0.407(.492)	1944	0(.00)	288	.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 2001-2007; "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 2001-2007, 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. All prices are in 2001 CFA. The Kolmogorov-Smirnov test tests for the equality of the distribution functions.

Table 3. Differences in Pre-Cell Phone Trends in Price Dispersion by Cell Phone Treatment Period

Dependent variable: ***Price dispersion at time t***	**Coef. (s.e.).**
Market Pairs Treated Year 1*Change in Pre-Treatment Years	10.00***(2.01)
Market Pairs Treated Year 2*Change in Pre-Treatment Years	2.318(4.45)
Market Pairs Treated Year 3*Change in Pre-Treatment Years	-.1592(2.92)
Market Pairs Treated Year 4*Change in Pre-Treatment Years	-2.477(2.27)
Market Pairs Treated Year 5*Change in Pre-Treatment Years	1.245(2.23)
Market Pairs Never Treated*Change in Pre-Treatment Years	-2.318(4.45)
R^2	0.0173
# of observations	7416

Notes: Data from the Niger trader survey and secondary sources collected by the author. Each row represents the year in which a specific market pair first received coverage, interacted with the change between the pre-treatment years (1999/2000 until 2000/2001). *E.g.,* "markets treated year 1" represents the market pair that received cell phone coverage in 2001, the first year of cell phone coverage. 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.

Table 4. 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	-4.55*** (1.04)	-.024* (.012)	-4.66*** (1.05)	-.024* (.013)	-1.42* (.863)	-1.869* (.995)	-.403 (1.01)
Transport costs (CFA/kg)	.386 (.264)		.399 (.281)		0.487* (.279)	-.164 (.364)	-.125 (.357)
Drought Dummy	4.02*** (1.48)	.0795*** (.009)	4.03** (1.49)	.080*** (.009)	-3.79** (1.62)	-.265 (1.73)	-4.152** (1.89)
Gas price (CFA/kg)	.0131 (.013)		.0123 (.014)			.0150 (.018)	.109 (.030)
Lagged dependent variable						-.237*** (.010)	-.239*** (.011)
Constant	0.800*** (.079)	-.0012*** (.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	2502	27342	2393	27342	24715	24715
# of cross-sectional observations	433	31	433	31	433	433	433
R^2	0.0079	0.3117	0.0079	0.3123	0.1006		
Joint effect						-2.433*** (.997)	-.325 (.816)
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 in 2001 CFA.

Table 5. Variation in Treatment Effect of Cell Phones by Gas Price Shocks, 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 Unpaved	(10) Both Paved
Cell Phone Dummy	-4.498*** (1.01)	-2.02** (.859)	-2.837** (1.20)	-.821 (1.10)	-1.454 (2.07)	-2.162** (1.01)	2.051 (2.23)	.598 (.862)	-3.665*** (1.62)	.796 (.862)
Cell*Gas price (CFA/kg)	.009 (.681)	1.03 (.731)								
Gas price (CFA/kg)	-.338 (.542)	-1.58*** (.525)	.012 (.013)	.073** (.028)	.002 (.065)	-.011 (.025)	.088 (.116)	.073** (.028)	.107*** (.025)	.015 (.031)
Cell*Distance Dummy			-3.875* (2.13)	-1.35 (1.81)						
Cell*Road Quality (unpaved road==1)								-3.478** (1.62)		
Road Quality (unpaved road=1)								.0345 (.052)		
Transport Costs	.641*** (.150)	.500** (.279)	.401 (.276)	.497* (.281)	8.589 (7.87)	.535 (.493)	-.1492 (1.24)	.495 (.261)	-1.59*** (.530)	1.374*** (.412)
Drought dummy	4.00*** (1.48)	-3.78** (1.62)	4.015** (1.48)	-3.78** (1.62)	-7.11 (6.31)	-3.08* (1.95)	-6.063** (3.07)	-3.822** (1.61)	4.903 (3.17)	-7.077*** (2.82)
Constant	.8043 (.080)	5.122 (.751)								
Common Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group-specific time trend	No	Yes	No	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	0.008	0.1007	27342	27342	2176	20079	5087	27342	15019	12323
# of cross-sectional observations	433	433	433	433	35	318	80	433	262	171
R^2	27342	27342	0.008	0.1007	0.0826	0.1000	0.2037	0.1008	0.1398	0.1084
Joint effect	-4.48** (1.01)	-1.95** (.850)	-6.71*** (1.77)	-2.17 (1.42)				-2.879** (1.38)		
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 6. 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	-.011 (1.10)	.0002 (.021)	-1.259 (1.11)	.0001 (.021)
Cell Phone Dummy*Network	-11.72*** (3.03)	-.0493 (.022)	-.2431 (2.92)	-.0493** (.022)
Transaction costs	.391* (.265)		.4871 (.261)	
Drought	4.04** (1.49)	.0766*** (.009)	-3.81** (1.61)	.076*** (.008)
Gas price (CFA/kg)	.0133** (.013)			
Constant	.7659*** (.079)	-.0010 (.000)		
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	0.0083	0.3181	0.1004	0.3181
Joint effect	-1.80** (.92)	-0.05*** (.012)	-1.30 (.876)	-0.05*** (.012)
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 in 2001 CFA.

Table 7. DD Estimates of the Impact of Cell Phones on Price Dispersion by Year

	Panel A: Price dispersion in 2001/2002		
	Cell Phone Mean	**Non-Cell Phone Mean**	**T-C (s.e.)**
Before treatment, mean(s.d.) 2000/2001	29.91 (9.64)	21.18 (16.17)	7.766***(1.84)
After treatment, mean(s.d.) 2001/2002	33.69(15.19)	25.199 (17.2)	8.498***(1.83)
After-before difference (DID) (s.e.)	3.78	3.053***(1.13)	1.182(1.23)
% change in price dispersion	12.64%	14.40%	5.57%
	Panel B: Price dispersion in 2002/2003		
	Cell Phone Mean	**Non-Cell Phone Mean**	**T-C (s.e.)**
Before treatment, mean(s.d.) 2000/2001	21.80(15.9)	22.15(16.5)	-.3411(3.72)
After treatment, mean(s.d.) 2002/2003	26.50(19.57)	25.96(20.8)	.5414(5.50)
After-before difference (DID) (s.e.)	4.69**(2.42)	3.82**(1.19)	1.582(2.62)
% change in price dispersion	21.51%	17.16%	7.13%
	Panel C: Price dispersion in 2003/2004		
	Cell Phone Mean	**Non-Cell Phone Mean**	**T-C (s.e.)**
Before treatment, mean(s.d.) 2000/2001	20.70(16.9)	22.15(16.49)	-1.44(2.43)
After treatment, mean(s.d.) 2003/2004	18.66 (13.08)	21.41(15.09)	-2.74(1.93)
After-before difference (DID) (s.e.)	-2.03(1.35)	-.7339(1.31)	-1.30(1.87)
% change in price dispersion	-9.81%	-3.31%	-5.87%
	Panel D: Price dispersion in 2004/2005		
	Cell Phone Mean	**Non-Cell Phone Mean**	**T-C (s.e.)**
Before treatment, mean(s.d.) 2000/2001	19.06(15.74)	22.15(16.4)	-3.077(2.01)
After treatment, mean(s.d.) 2004/2005	23.44(19.26)	29.35(23.0)	-5.906***(1.87)
After-before difference (DID) (s.e.)	4.376(.817)	7.204(1.28)	-3.435***(1.65)
% change in price dispersion	22.93%	32.52%	-15.49%
	Panel E: Price dispersion in 2005/2006		
	Cell Phone Mean	**Non-Cell Phone Mean**	**T-C (s.e.)**
Before treatment, mean(s.d.) 2000/2001	20.41416.9)	22.15(16.49)	-1.731(1.92)
After treatment, mean(s.d.) 2005/2006	20.113(14.56)	22.37(15.98)	-2.26(1.28)
After-before difference (DID) (s.e.)	-.3014(.518)	.2289(1.33)	-.8273(1.34)
% change in price dispersion	-1.48%	1.03%	-3.73%

Notes: Data from the Niger trader survey and secondary sources collected by the author. 'Cell phone" is defined as those market pairs having cell phone coverage in that particular year. "No cell phone" is defined as those market pairs that never received cell phone coverage over the entire period. The "percent change" is calculated as the after-before difference compared to the no cell phone price dispersion in the pre-treatment period. Huber-White robust standard errors clustered at the market pair-month level in parentheses. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are in 2001 CFA.

Table 8. 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) Propensity Score**
Cell Phone Dummy	-5.77*** (1.29)	-5.675*** (1.28)	-2.73*** (1.05)	-1.88* (1.05)	'-1.195 (1.68)	-2.80* (1.71)
Cell Phone Dummy*Network					-4.14 (4.09)	2.302 (3.58)
Constant trend	Yes	Yes	Yes	Yes	Yes	Yes
Group trend	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Dummy	No	No	Yes	Yes	Yes	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	0.1	0.103	0.103
%Δ	-26.05%	-25.60%	-12.33%	-8.49%	-10.43%	-11.06%
Joint effect (cell and network):					-2.31* (1.32)	-2.45* (1.32)

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 in 2001 CFA.

Table 9. 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	-.1167 (2.12)	-0.05
Conditional difference in means	.2022 (1.95)	0.1
Propensity score regression	-.9770 (2.04)	-0.48
Propensity score regression with demeaned propensity score	-.9770 (2.03)	-0.48
Weighting and regression	.6685 (1.20)	0.56
Weighting and regression with additional covariates	1.653 (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 in 2001 CFA.

Table 10. DD Estimates of Cell Phone Effects Controlling for SUTVA Violations

Dependent Variable: ***Price dispersion between markets at time t***	**Tillaberi**			**Zinder**			**Tillaberi-Zinder**		
	(1) OLS estimate	**(2) WLS estimate**	**(3) Propensity Score Matching estimate**	**(4) OLS estimate**	**(5) WLS estimate**	**(6) Propensity Score Matching estimate**	**(7) OLS estimate**	**(8) WLS estimate**	**(9) Propensity Score Matching estimate**
Cell Phone Dummy	-10.54***	-11.62***	-10.43**	-6.90**	-4.05**	-5.98**	-11.02***	-12.13***	-10.92***
	(3.90)	(3.88)	(3.89)	(2.18)	(1.37)	(2.79)	(4.05)	(4.36)	(4.05)
Common Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group-specific time trend	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No
Market-Pair Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of observations	786	786	786	542	249	269	1050	1050	1050
# of cross-sectional obs	13	13	13	7	7	7	14	14	14
R^2	0.2543	0.2633	0.2543	0.2873	0.3699	0.3699	0.1441	0.149	0.1442

Notes: Data from the Niger trader survey and secondary sources collected by the author. "Cell phone dummy"=1 at time *t* if both markets received cell phone coverage, 0 otherwise. Columns 1-3 compare cell phone markets in Tillaberi with non-cell phone markets in Tillaberi. Columns 4-6 show the same analysis, but for Zinder. Columns 7-9 compare cell phone markets in Tillaberi with non-cell markets in Zinder. 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.

Table 11. 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	.058(.235)	.126(.333)	.068(.06)	.068(.914)
Education (0=elementary or above, 1=no education)	.663(.475)	.608(.488)	-.054(.08)	.054(.989)
Age	44.60(10.75)	46.01(12.6)	1.409(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)
Trader type (wholesaler, semi-wholesaler, intermediary, retailer)	3.04(1.16)	2.96(1.15)	.080(.166)	.061(.962)
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	.139(.346)	.064(.246)	.075*(.039)	.075(.877)
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 association	.345(.476)	.296(.459)	.049(.074)	.049(.998)
Panel B. Market-Level Characteristics				
Distance to paved road greater than 75km	.045(.208)	.045(.208)	-.106(.116)	.106(.438)
Road quality	.453(.500)	.793(.406)	.339(.200)	.339***(0.00)
New paved road over the past 5 years	.333(.472)	.406(.494)	-.074(.224)	0.074(.859)
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 12. 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 only 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 13. 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)

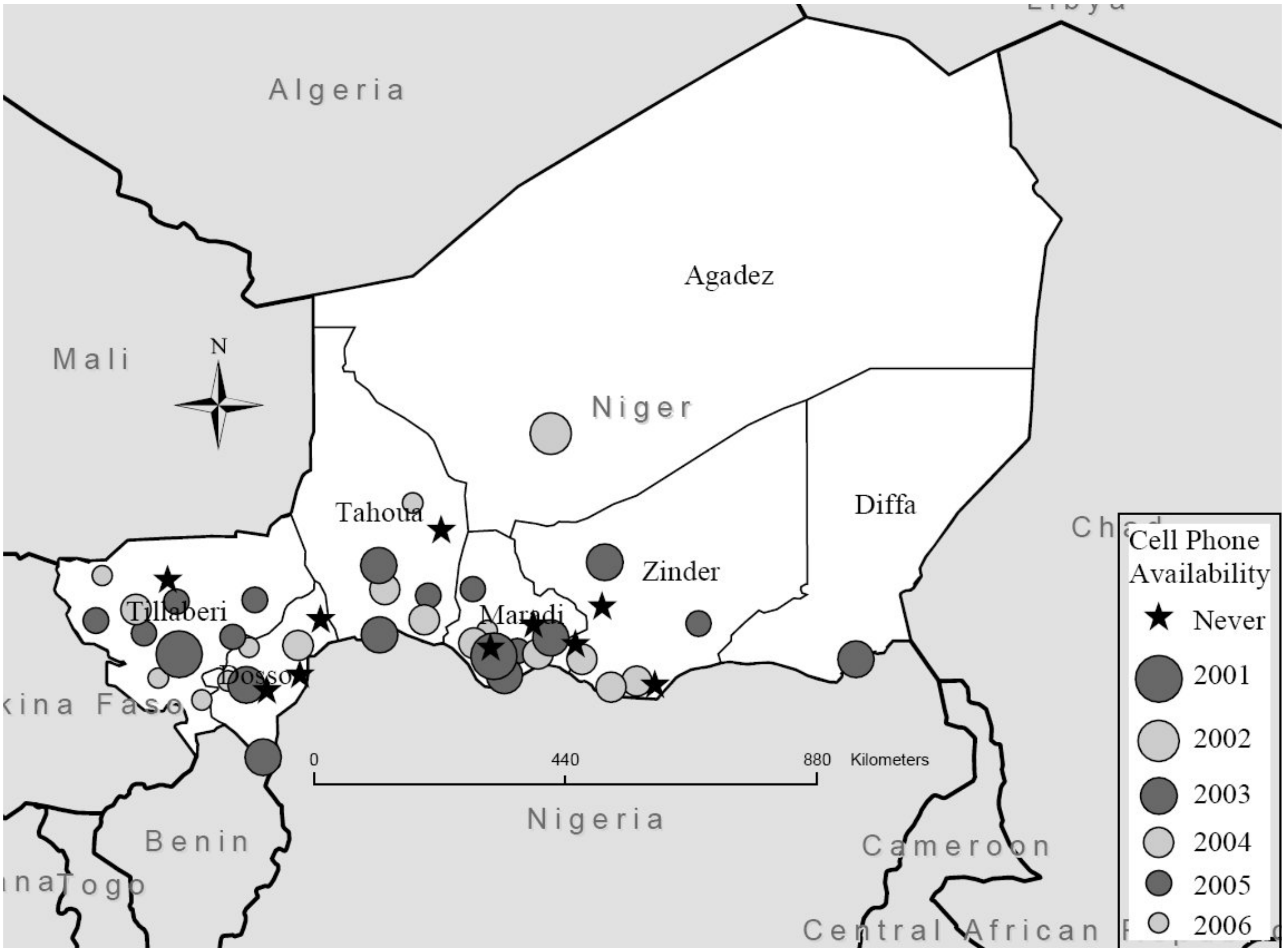
Notes: Data from the Niger trader survey and secondary sources collected by the author. "Cell phone" dummy is a binary variable equal to 1 if the market had cell phone coverage in 2005, 0 otherwise. The untrimmed treatment effect is the difference in the weighted means of traders in cell phone and non-cell 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. 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 14. DD Estimates of the Impact of Cell Phones on Grain Prices, 2004/2005

	(1) All Regions	(2) Food Crisis Regions	(3) Non Food Crisis Regions
Grain Price (CFA/kg)	-4.06***(2.04)	'-7.47*(4.07)	-4.52(16.0)
CV	-.024**(.012)	-.025(.029)	-.050***(.011)

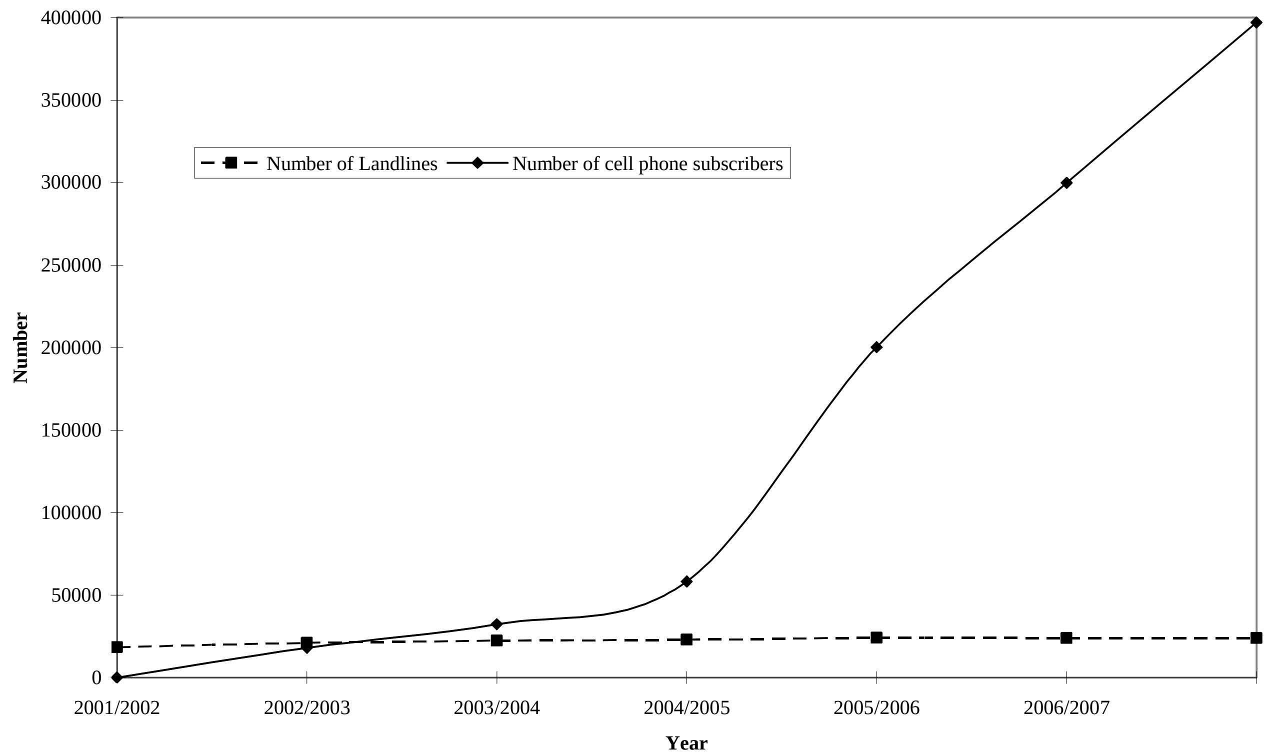
Notes: Data from the Niger trader survey and secondary sources collected by the author. Cell phone market pairs are those cases where both markets received cell phone coverage at some point between 2001-2007; no cell phone market pairs are those pairs where either one or both markets never received cell phone coverage. * is significant at the 10% level, ** significant at the 5% level, *** is significant at the 1% level. All prices are in 2001 CFA.

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



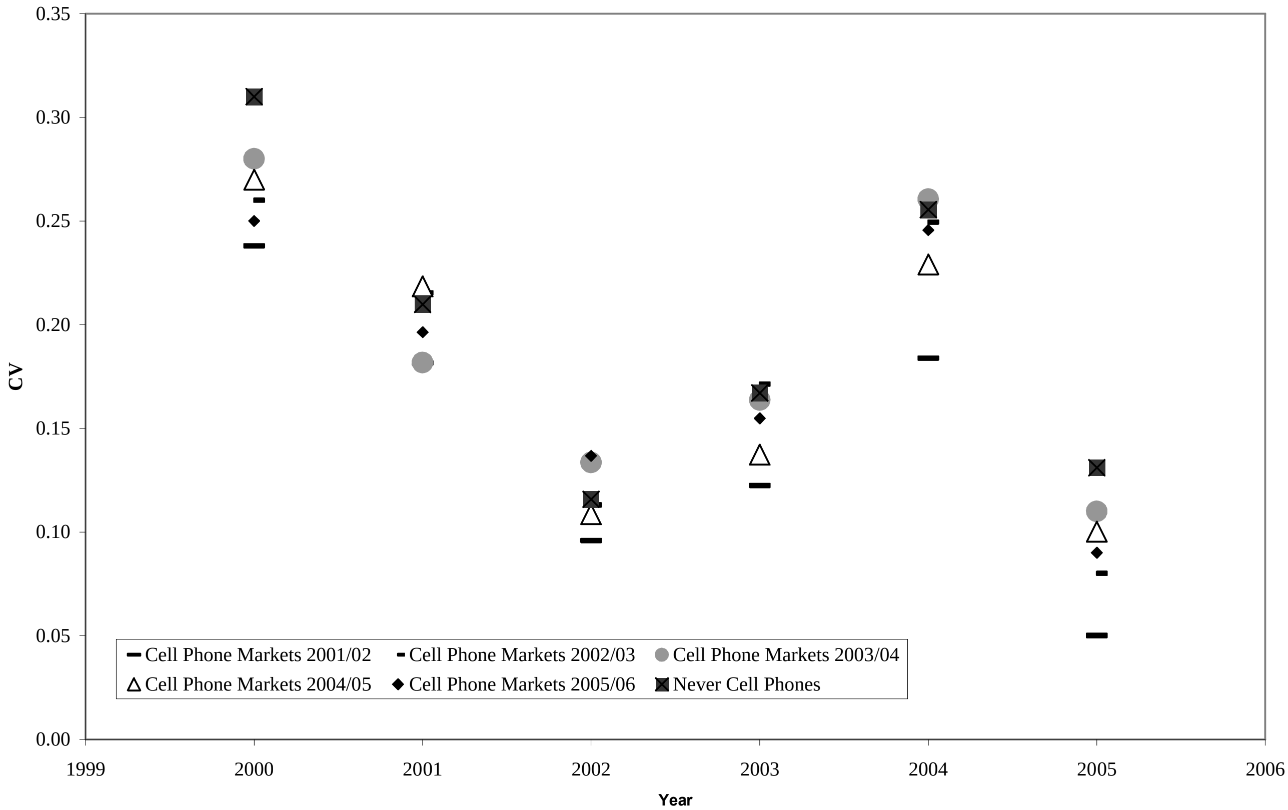
Notes: Data collected by the author from cell phone companies in Niger (Celtel, Telecel and Sahelcom). The map shows cell phone coverage for all major grain markets between 2000-2006, but not all towns and cities in Niger.

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



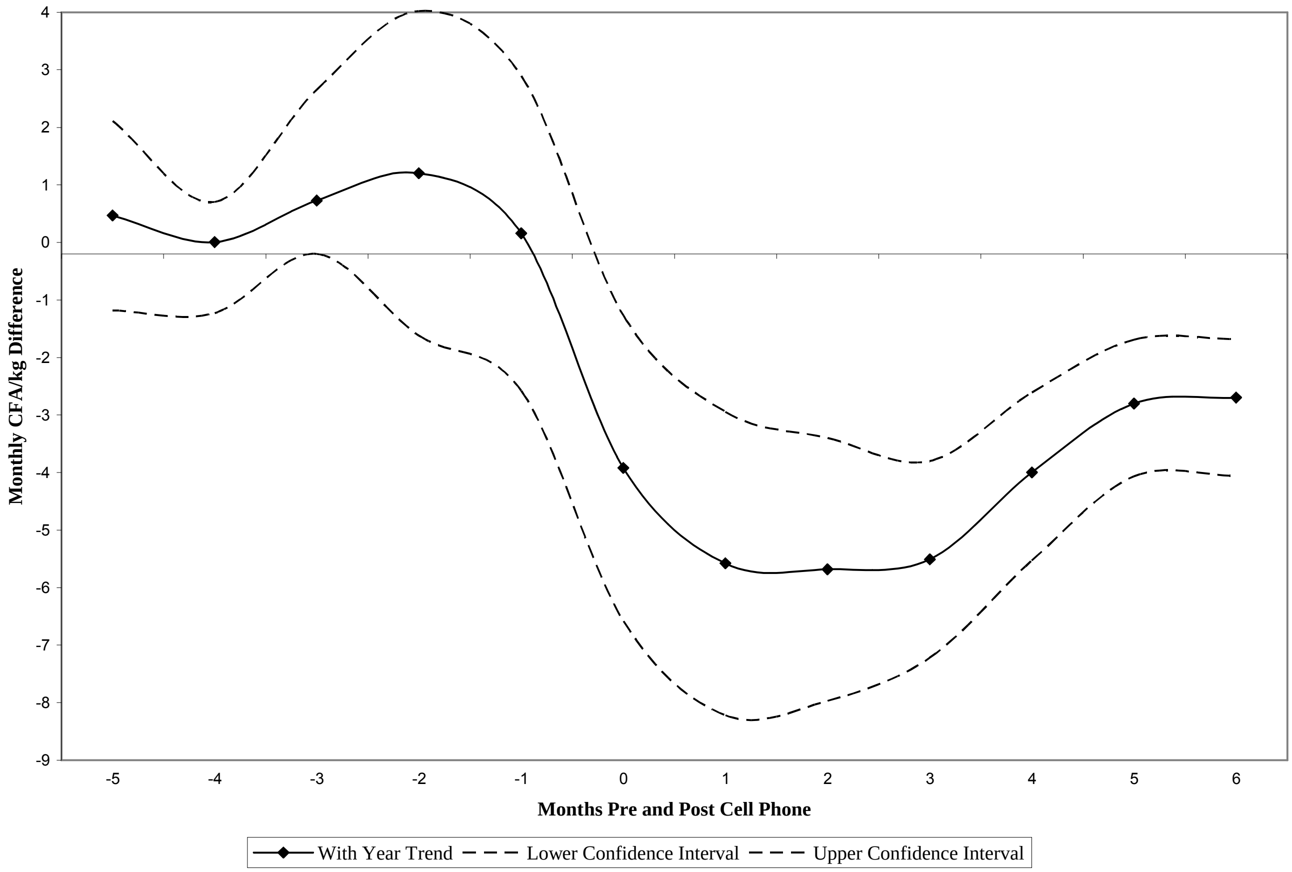
Source: Data collected by the author from the *Société Nigérienne des Télécommunications* (SONITEL) and secondary sources.

Figure 3. Changes in the Coefficient of Variation by Cell Phone Group



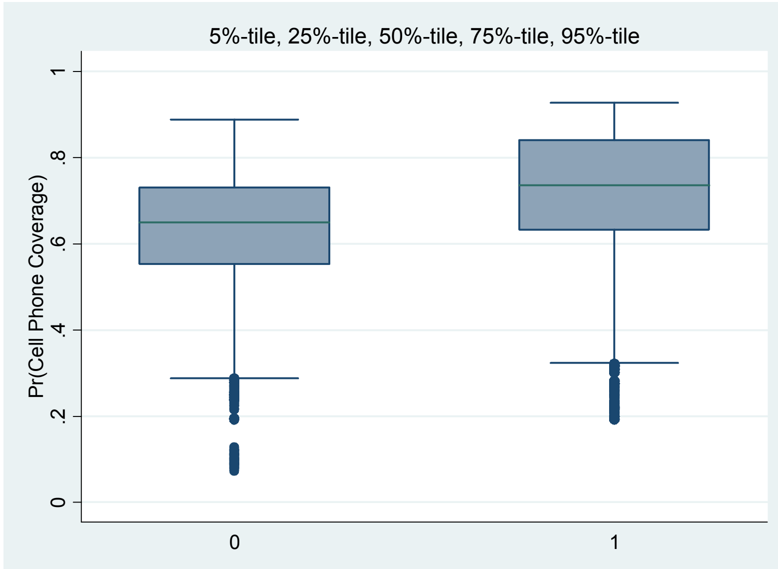
Notes: Data from the Niger trader survey and secondary sources collected by the author. "Cell phone markets" are those markets that received cell phone coverage at some point between 2001-2006; "Never cell phones" are those markets that never received cell phone coverage during the entire period. Each year represents an agricultural marketing season: *e.g.*, 2000=2000/2001, "2001"=2001/2002, "2002"=2002/2003, and so on. Markets are divided into 6 categories, based upon the year that they first received cell phone coverage. E.g., "Cell Phone Markets 2001/02" are the markets that received coverage during the first year. "Cell Phone Markets 2002/03" are the markets that received cell phone coverage during the second year of coverage. The coefficient of variation (CV) is calculated as the intra-annual standard deviation of grain prices on a market divided by the mean grain price on that market for each year.

Figure 4. Changes in Price Dispersion Pre- and Post-Cell Phone Coverage (OLS Coefficients on Event Dummies)



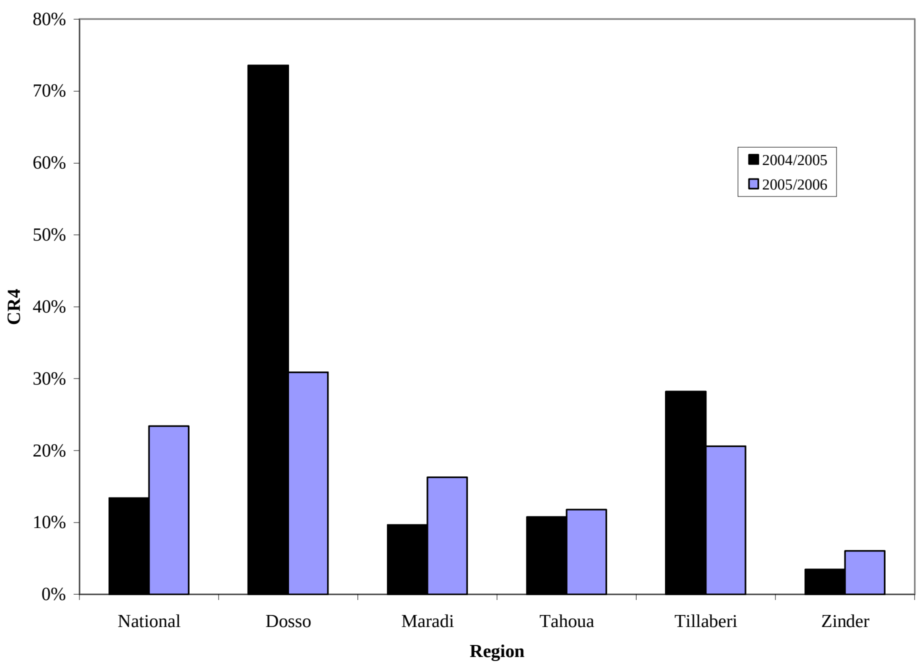
Notes: Based upon the regression of price dispersion on dummy variables pre and post-cell phone coverage. Upper and lower confidence intervals are shown. No parametric smoothers were used.

Figure 5. Comparison of Box Plots of the Propensity Score by Cell Phone Coverage



Notes: The propensity scores are estimated using a parsimonious probit, regressing treatment assignment (a cell phone tower) on pre-treatment covariate regressors, including transport costs, distance, drought, road quality, market size, urban center and an interaction term between transport costs and road quality.

Figure 6. Four-Firm Concentration Ratio 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. The CR4 was calculated for each market in the sample (N=35) using following formula: (4 * total purchase of the largest trader in the sample) / (total purchases by all traders surveyed in the market * total number of traders operating in the market/number of surveyed traders). The regional CR4 was then obtained by an unweighted average of the market-specific CR4s. Kohls and Uhl (1985) suggest that a four-firm concentration ratio (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 in 2004/2005. However, this was primarily due to the non-competitive structure of a market located on the border with Nigeria (Wadata).

Appendix A. Derivation of Comparative Static Results of the Theoretical Model

1. Proposition 1. $\dfrac{dr}{dc} < 0$

The reservation function is defined as: $h(r) = B(r) - c$

$$\Rightarrow [u(\bar{p} - \tau k_{r+1}) - u(r - \tau k_r)] - \int_{r+\tau(k_{r+1}-k_r)}^{\bar{p}} F(p)u'(p - \tau k_{r+1})dp = c$$

Taking the total derivative of this expression with respect to *r* and *c* yields:

$$[-u'(r - \tau k_r) + F(r + \tau(k_{r+1} - k_r))u'(r + \tau(k_{r+1} - k_r) - \tau k_{r+1})]dr = dc$$

$$\Rightarrow [-u'(r - \tau k_r) + F(r + \tau(k_{r+1} - k_r))u'(r - \tau k_r)]dr = dc$$

$$\Rightarrow \frac{dr}{dc} = \frac{1}{u'(r - \tau k_r)[F(r + \tau(k_{r+1} - k_r)) - 1]} \leq 0$$

Since $u'(r - \tau k_r) > 0$ and $F(r + \tau(k_{r+1} - k_r)) \leq 1$. This is strictly decreasing if $F(r + \tau(k_{r+1} - k_r)) < 1$. Therefore, a decrease in search costs leads to a decrease in the reservation price. Q.E.D.

2. Proposition 2. $\dfrac{dE(n)}{dc} < 0$ [64]

For the n^{th} search, the trader's probability of finding a satisfactory price is $1 - F(r + \tau k_n)$. Assuming that draws are independent and sampling without replacement, the probability of *n-1* failures and success on the n^{th} search is $\Pr(p_1 - \tau k_1 < r;..; p_{n-1} - \tau k_{n-1} < r; p_n - \tau k_n \geq r)$, which can be written as:

$$\left(\prod_{i=1}^{n-1} F(r + \tau k_i)\right)\left(1 - F(r + \tau k_n)\right)$$

With τ =0, this simply reduces to $\Pr(\hat{p} > r) = F(r)^{n-1}(1 - F(r))$, which is a geometric distribution with mean equal to $1/(1 - F(r))$. Then, the expected number of searches required to find a price *higher* than the reservation price is $E(n) = \dfrac{1}{(1 - F(r))}$. Taking the derivative with respect to *r* yields

$$\frac{dE(n)}{dr} > 0, \text{ and } \frac{dE(n)}{dc} = \frac{dE(n)}{dr} * \frac{dr}{dc} < 0$$

Therefore, a decrease in search costs will lead to an increase in the expected number of markets over which traders search. Q.E.D.

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64 Under sampling *with* replacement, $\Pr(\hat{p} > r) = F(r)^{n-k}(1 - F(r))$, where $k = 1 + \sum_{j=1}^{n-1}(n_j - 1)$, and n_j is the number of times market j was sampled.