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## Impact of Mobile Phones on Staple Food Markets in Mozambique: Improved Arbitrage or Increased Rent Extraction?

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# Impact of Mobile Phones on Staple Food Markets in Mozambique: Improved Arbitrage or Increased Rent Extraction?

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# **Impact of Mobile Phones on Staple Food Markets in Mozambique: Improved Arbitrage or Increased Rent Extraction?**

Wouter Zant\*

## **Abstract**

I use the quasi experimental nature of the roll-out of the mobile phone network in Mozambique to estimate the impact of search costs on the dispersion of maize prices and transport costs. The introduction of mobile phone services from 1997 to 2009 explains a 4.5-11% percent reduction in price dispersion of maize prices, and a slightly larger reduction in per ton km transport costs. Apart from an improvement of the efficiency of maize markets, the evidence suggests that traders benefit by capturing increased rent income. Various sources of potential heterogeneity are identified: the reduction is larger for pairs connecting remote locations, for source markets with a low poverty head count and with a higher mobile phone coverage in neighbouring markets, and during drought periods.

JEL code: O13, O33, Q11, Q13

Key words: search costs, transport costs, mobile phones, agricultural markets, maize prices

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## **Introduction**

This paper investigates the hypothesis that a decrease in the costs of information, due to the introduction of mobile phones, improves spatial arbitrage and efficient operation of markets. In particular I estimate the impact of mobile phones on price dispersion of maize prices and grain transport costs in Mozambique. Mobile phone infrastructure was rolled out in Mozambique from 1998 to 2010. Traditionally, information on maize prices across markets in poor countries like Mozambique is collected by traders travelling to markets, through word-of-mouth and through personal and professional networks. The new available communication technology allows traders to assess maize prices in distant markets quickly, efficiently and at low costs. Improved information as a result of lower search costs leads to a reduction of transport costs and also to a reduction of price dispersion across markets.

In order to identify the impact of mobile phones on dispersion of agricultural prices, I exploit the quasi experimental nature of the rollout of the mobile phone infrastructure. I will argue that the conditions for a natural experiment are met, particularly in the course of the development of the mobile phone network, after a few initial years. In the first place a standard difference-in-difference approach (diff-in-diff) is applied to estimate impacts. In order to address possible selection bias in the data, diff-in-diff is complemented with propensity score matching.

For the impact estimations I use weekly recorded data of maize prices and transport costs, respectively for the period 1997-2007, and 2001-2010. For a variety of transformations, exercises and tests, these core data are complemented with data on distance between markets, population, rainfall, fuel prices, poverty and consumer prices. A few additional variables, like mobile phone network density and road quality are constructed. With the exception of mobile phone rollout and rainfall data, all data are obtained from public domain sources.

I find that the introduction of mobile phones in Mozambique has reduced dispersion in maize prices with 4.5-11 percent and per ton kilometer transport costs slightly more. Assuming that price differences are equivalent to transactions costs, and transactions costs are the sum of transport costs, rents of traders and other transactions costs, this outcome suggests improved arbitrage jointly with increased rents extraction by traders. The evidence further suggests that impacts are larger for markets that are more remote, for source markets with a lower poverty head count, for source markets with a higher density of the mobile phone network and during drought periods. The results due not unambiguously indicate a different impact north of the Zambezi compared to south of the Zambezi.

The research in this paper is related with various other contributions on the impact of mobile phones on agriculture in developing countries (see e.g. Jensen, 2007; Muto and Yamano, 2009; Aker, 2010; Fafchamps and Minten, 2012; Fafchamps and Aker, 2014; Aker and Ksoll, 2016). The current work offers additional evidence on this topic and differs from previous work in its attempt to explain (the difference in) impact on price dispersion and impact on transport costs.

The rest of this study proceeds as follows. Section 1 discusses the empirical literature on search costs and on the role of mobile phone technology. Section 2 presents the background on maize marketing and maize trade in Mozambique, and the introduction of mobile phones in Mozambique. Section 3 presents the data, elaborates the methodology and the empirical strategy. Section 4 presents the impact estimations, shows heterogeneity in impacts and presents robustness checks. Section 5 discusses results and presents the summary and conclusion.

## **1. Search Costs, Mobile Phones, Transport Costs and Staple Food Prices**

There is a growing body of empirical work on the impact of mobile phones and related information technology on trade and agriculture in developing countries (Jensen, 2007; Muto and Yamano, 2009; Aker, 2010; Fafchamps; Fafchamps and Minten, 2012; Aker and Fafchamps, 2014; Tadesse and Bahiigwa, 2015; Aker and Ksoll, 2016). This empirical work is based both on experimental (RCTs) and non-experimental data, in the latter case exploiting the roll out of mobile phone infrastructure as a natural experiment, or employing estimation techniques designed for non-experimental data. The overall conclusion, thus far, is that the introduction of mobile phones has caused a decrease in price dispersion (and hence an increase in efficiency of markets), most likely due to increased trader activities. However, it is much less clear if behaviour of farmers has been affected and if farmers are benefiting from access to mobile phones. Jensen (2007) makes use of micro level survey data to show that price dispersion on fish markets in Kerala, India has dramatically reduced after the introduction of mobile phones, increasing fishermen's profits and consumer welfare. Easy and timely access to information is also shown to prevent waste, inefficiency and spoilage of production of perishable crops (Overa, 2006; Jensen, 2007; Muto and Yamano, 2009). Muto and Yamano (2009) investigate marketing costs of maize and bananas during the introduction mobile phones in Uganda, using household data for 2003 and 2005, and show increased market participation of farmers in remote areas, but no other impacts on maize marketing. Asymmetric information between traders and farmers is suggested to block potential benefits for farmers. Aker (2010) finds that price dispersion across Niger millet markets experienced a 10-16% reduction after the introduction of mobile phones, due to traders' activities. The reduction in price dispersion is shown to be stronger for market pairs that are farther apart and if roads have lower quality. Reduction in price dispersion is also shown to be larger once a critical mass of market pairs has mobile phone coverage. The lower reduction in price dispersion compared to Jensen (2007) is

attributed to better storability of grain and lesser perishability than fish. Fafchamps and Minten (2012) estimate the benefits for farmers of SMS based agricultural information in Maharashtra, India, using a randomized controlled trial. The information includes prices, weather forecasts, crop advice and new items. They find no effect of this service on the prices received by farmers, value added, crop losses, crop choices and cultivation practices. These disappointing and somewhat disturbing results are in line with the limited commercial take-up of the information service, but difficult to reconcile with previous investigations on the impact of information (as documented above). A comparative advantage in transport is suggested as an explanation why benefits accrue in the first place to traders and not to producers. Aker and Fafchamps (2014) find that the introduction of mobile phones in Niger reduced dispersion of farm gate prices for a semi-perishable crop (cow peas), but does not affect price dispersion of storable crops (millet and sorghum). Also levels of farm gate prices are not affected, while variation in prices over the years is reduced.

The current study further verifies the impact of mobile technology on price dispersion for a different country (Mozambique) and additionally assesses if and to what extent the reduction in price dispersion corresponds with a reduction in transport costs. Under conditions of trade between markets one would expect the impact on transport costs, one of the major components of transaction costs, to be smaller than the impact on transaction costs (which is equivalent to the price difference between markets).

## **2. Mozambique Maize and Marketing, and Mobile Phone Rollout**

### *Maize and Marketing*

Maize is the most important staple food of Mozambique: it is most widely produced, marketed, exported and consumed. In all provinces two third of all rural households produce maize, maize is three times more marketed than cassava and maize has a budget share of



similar size as all other staple foods<sup>1</sup> together (Tschirley et al., 2006). The calorie share of maize in the average Mozambique diet ranges from 25% to 39%, corresponding with a per capita (annual) consumption of 60 to 85 kg, although, particularly in the south, and in the Maputo region, the maize share is lower due to substitution with rice (Tschirley et al., 2006).

Domestic production of maize is concentrated in the central and northern part of Mozambique (for a map of Mozambique, see Appendix, Figure A1). The Northern provinces Niassa, Cabo Delgado, and Nampula have better rainfall distribution and better soil fertility, while the Southern region has unfavorable weather conditions and suffers from occasional pests (Abdula, 2005). Most agricultural production in Mozambique is rain-fed. Drought and also flooding cause occasional drops in production. In the 1999-2000 crop season, maize production declined 18 percent, due primarily to floods that devastated large areas of the Center and South of the country (Abdula, 2005). Major production, assembly and wholesale markets in the central region are Manica, Chimoio and Gorongosa, and in the north Alto Molocue, Montepuez, Mocuba and Ribaue. Due to widespread subsistence farming only a limited share of production (around 30% of production) is traded on the market. The major retail terminal markets, nearly all on the seaside, are, from south to north, Maputo (including Matola), Xaixai, Maxixe, Massinga, Beira, Quelimane, Nacala and Pemba.

Maize is mainly transported by trucks. The road infrastructure is, however, not well developed, and especially during the rainy season many roads cannot be used. The Zambezi river creates a natural barrier to domestic trade: major domestic trade flows of maize are from the central area to the south, the major deficit area, while the northern cities at the seaside are supplied by the more inland production centers in the north. Angonia in the northeast, also a major production, assembly and wholesale market, supplies Tete, while from both Angonia and Lichinga region maize is exported to Malawi (USGS / FEWS NET). Trade costs data

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<sup>1</sup> Staples in Mozambique are maize, rice, cassava, wheat, sorghum and millet.

(SIMA) confirm these stylized facts<sup>2</sup>. Southern Mozambique, and most notably the Maputo-Matola area, is a major maize deficit area.

Maize available for sale in wholesale markets in Maputo (Xiquelene and others) is, amongst other locations, sourced from the central region, Nhamatanda, Chimoio or Manica, around 1100 km by road (Abdula, 2005; SIMA data from 1999-2001), or even as far as Tete, around 1500km by road from Maputo (Tostão and Brorsen, 2005; SIMA trade flow data from 1998-2001). The itineraries of the SIMA transport cost data used in this research extend as far as the distance between Lichinga and Maputo (by road around 2300km!)<sup>3</sup>. Southern Mozambique, and the Maputo-Matola area in particular, rely also on South Africa as a key supplier of maize (see Haggblade et al., 2008).

The milling industry, defunct until the late 1990s (processed maize meal sold on the market was imported), re-started with the privatization of CIM (Compania Industrial de Matola), the company that subsequently dominated the maize meal market for a long period. With only few other millers entering the market despite high retail prices and margins for CIM, concentration in the milling industry only slowly reduced in the following decades. Since supply of domestic maize in the urban south is expensive (transport costs), of low quality and unreliable, the milling industry depends on maize grain imports, mainly from South Africa. An import policy regime favourable to large industrial maize millers (and phased out in 2015), further contributed to privileged position of millers (Tschirley et al., 2006).

#### *Mobile phone rollout*

Similar to most other sub-Saharan countries (ITU, 2016), mobile phone technology was introduced in Mozambique at the end of the 1990s and early 2000s, notably rollout in

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<sup>2</sup> Trade cost data are available for selected itineraries (see data and methodology section). The itineraries for which transport cost data are available, are likely to correspond to the major trade flows.

<sup>3</sup> In the estimations in the empirical section I have also shown how imposing a maximum trading distance affects the estimation results (see Appendix Figure A6 and A7).

Mozambique stretches from 1997 to 2006. During the first three years (1997-1999) mobile phone towers were installed exclusively in the Maputo area: In observing sound returns to investments, mobile phone companies concentrated on locations with high population density, in the early development of the network. In later years the network was extended to less populated and more remote areas<sup>4</sup>. During this period average mobile phone network density<sup>5</sup> in Mozambique as whole increased 5 to 6 fold. The number of phone customers (mobile-cellular telephone subscriptions) in Mozambique increased from 51,065 in 2000 to a staggering 7,224,176 in 2010 (ITU, 2016), corresponding with an increase in the share of the population from 0.3% in 2000 to 30.1% in 2010. According to western standards (above 100%) still a modest share, but light years away from the stagnant land line coverage of less than 0.4% (fixed telephone subscriptions in 2010: 88,062). The success of the introduction of mobile phones in sub-Saharan African countries is due to the low prices of mobile phones and the low cost of mobile phone use, partly related to the distribution of pre-paid cards for very small amounts, and the introduction of pre-paid system that has solved the cashing problem (a key problem with land lines). Despite the reasonably low costs of mobile phones and mobile phone use<sup>6</sup>, it is likely that use and access to mobile phone services is biased against the poor. This is also supported by the empirical evidence in this study (see empirical estimations).

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<sup>4</sup> The initially endogenous rollout of the cell phone network has consequences for the empirical analysis: see section on data and methodology.

<sup>5</sup> Cell phone network density = the sum of surrounding locations with cell phone facilities divided by the distance to these locations, for each location with cell phone facilities. I measure population weighted cell phone network density (by source market), provided that the source market has cell phone facilities.

<sup>6</sup> At the time of writing (2016) the price of a simple mobile phone is around 400 Mt (around 5-6US\$) and a local phone call around 6Mt per minute (less than US\$ 0.10).

### 3. Data and methodology

#### *Data sources*

The data on the rollout of mobile phone infrastructure are sourced from the Ministry Of Telecommunications of Mozambique<sup>7</sup>, contain 547 names of locations of mobile phone towers, their corresponding latitude and longitude coordinates and first year of operation. The rollout stretches from 1997 to 2009. During the first three year (1997-1999) mobile phone towers were installed exclusively in the Maputo area. This has some bearing on the analysis: at the start roll-out is guided primarily by population density and thereby endogenous. Only in the course of the years, after a critical network mass is achieved and most high density locations are supplied, further extensions can safely be assumed to be random. The range of a mobile phone tower (or Base Transceiver Station) is, roughly, limited to 35km, but could vary with the height of antenna over surrounding terrain, the frequency of signal in use and various other parameters<sup>8</sup>. I employ a range of 35 km (as the crow flies) around the mobile phone tower too identify markets that have mobile phone facilities. In order to identify market pairs between which mobile phone communication is feasible (in the empirical work) I require both source and destination markets to have mobile phone facilities.

Maize prices are from Sistema de Informação de Mercados Agrícolas de Moçambique (SIMA; [www.masa.gov.mz/sima](http://www.masa.gov.mz/sima)), from the weekly publication Quente-Quente<sup>9</sup>, in particular the weekly quotations of white maize retail prices (cuadro 3, preço e mudança percentual a nível de mercado retalhista (MT/kg), grão de milho branco), recorded for 27 markets<sup>10</sup>, from

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<sup>7</sup> Cell phone roll-out data were made kindly made available by Jenny Aker. With the exception of the cell phone roll-out data (and rainfall data), all data used for this research are public domain data.

<sup>8</sup> These other parameters include special equipment, the transmitter's rated power, uplink/downlink data rate of the subscriber's device, directional characteristics of the site antenna array, reflection and absorption of radio energy by buildings or vegetation, local geographical or regulatory factors and weather conditions.

<sup>9</sup> SIMA information is also available in newspapers.

<sup>10</sup> Alto Molocue, Angoche, Angonia, Beira, Chimoio, Chokwe, Cuamba, Gorongosa, Lichinga, Manica, Maputo, Massinga, Maxixe, Milange, Mocuba, Monapo, Montepuez, Mutarara, Nacala, Nampula, Nhamatanda,

January 1999 to December 2007. This period covers the period of the roll-out of mobile phone infrastructure. The price data are collected by interviewing randomly selected retailers in each market. Unfortunately, there are missings in the price data: overall we have more than 50% of the potential number of weekly observations, in total more than 6000 observations. A few markets have very few maize price data (Nhamatanda, Quelimane) and also a few months have no observations (May and June 2006), both for unclarified reasons. Please note, however, that the construction of spatial price differences – the price dispersion measure that is used in the estimations – blows up the number of available observations to around 40,000. Price developments over time, shown in the appendix (Figure A2), reflect price fluctuations related with the rain-fed character of agriculture. Prices peaked in 2002 and 2006 due to droughts. Moreover, there is strong seasonality in maize prices: prices begin rising around September reaching a maximum around March. The extent of seasonality, also shown in the appendix (Figure A3 to A5), is substantial with prices in the lean season twice as high compared to the post-harvesting months and corresponds with observed seasonality in staple food prices in other sub-Saharan countries (see Kaminski et al., 2016).

Data on transports are from the same source (SIMA), but are only available for a limited number of itineraries. Collection of these data is organized similarly to the collection of price data, by asking quotations from randomly selected traders in major source and destination markets. Transport cost data are specified by product (!)<sup>11</sup> and by the weight of the bags transported. Transport costs are recorded for the period August 2001 to December 2010, with nearly three quarter of the observations before 2005.

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Pemba, Quelimane, Ribaue, Tete, Vilanculos en Xai-Xai. A map in the Appendix (Figure A1) shows the locations of these markets in Mozambique.

<sup>11</sup> One would expect that the transport costs for a 100kg bag of maize is equivalent to the transport costs of a 100kg bag of beans. However, these costs are recorded separately.

The available trade cost data suggest that cities located on the seaside (primarily, Maputo (including Matola), Beira, Quelimane, Maxixe, Xai-Xai and Nacala, but also smaller cities in the coastal area) are major terminal destination markets; Alto Molocue, Nhamatanda, Angonia and Montepuez are the major source markets and Tete, Nampula and Chimoio are major transfer markets (both source and destination). This corresponds with FEWSNET documentation on assembly, wholesale and retail markets in Mozambique. To a certain degree the Zambezi river cuts the maize trade into a central southern part and a northern part (see also Tschirley et al., 2006; USGS / FEWSNET).

For descriptive purposes I have summarized the development over the years of maize price differences and transport costs between markets, deflated with the consumer price index, for selected itineraries (see Appendix, Table A2). The selection of itineraries is based partly on the availability of (sufficient) observations and partly on a prior about source and destination markets, derived from the empirical literature. Transport costs data do show a certain decrease over time, that corresponds with a reduction after the introduction of mobile phones. Price differences, however, only show a decrease over time for a few itineraries. Also before and after comparison of price differences does not underscore the expected impact of the introduction of mobile phones. Seasonality, between-year fluctuations and market pair related trends are apparently blur the underlying impact and these influences are much larger in the case of prices differences than in transport costs.

A number of other data from miscellaneous sources are used. Distance, both road distance and Euclidian distance (“as the crow flies”) in kilometres, and traveling time in hours is obtained from GoogleMaps, accessed at the time of implementing this study (2016)<sup>12</sup>. Road distance is relevant for transport costs, while we use Euclidian distance to measure the coverage of mobile phone towers. Road quality is obtained from combining road

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<sup>12</sup> Hence, changes in road infrastructure are not properly accounted for.

distance and traveling time. Decadal rainfall data (10 days) from 1995 to 2012 by district are from FEWSNET<sup>13</sup>. We use these data to model excess rainfall causing flooding, and drought due to a shortage of rain over the season. Data on population by city are from three censuses (August 1997, September 2007, July 2016), published by Instituto Nacional de Estatística Moçambique. Monthly series are obtained by interpolation. Population is used to model (relative) demand. Jointly with road distance between cities and mobile phone access, I also use population data to construct network densities. Fuel prices (annuals, limited number of years), exchange rates and consumer price indices are from International Financial Statistics of the IMF. Jointly with road distance, road quality and consumer prices, fuel data are used to verify and clean transport cost data (see Appendix Table A1). Poverty head count data are based on household surveys and sourced from van de Boom (2010) and Alfani et al. (2012).

#### *Methodology and empirical strategy*

I measure price dispersion as the positive maize price difference between market  $j$  and  $k$  in period  $t$ , in formula  $p_{j,t} - p_{k,t}$  for all  $p_{j,t} > p_{k,t}$ , for all markets for which  $j \neq k$ . I interpret the difference in price between markets as transaction costs, the sum of, amongst other things, costs of loading and offloading, transport, information and insurance and also potential rents extracted by agents in the market chain. Extraction of rents arises because information is not readily available and markets are not fully transparent. A major attraction of using positive price differences as the measure of price dispersion is its comparability with transport costs. It is assumed that the higher price pertains to destination markets and the lower price to source markets. The identification of source and destination markets on the basis of this assumption is not always in line with the stylized facts from the Mozambique maize marketing (see e.g. Abdula, 2005; Tschirley et al., 2006, FEWSNET, 2010). Following several reports on the Mozambique maize market, cities and towns on the coastline are

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<sup>13</sup> Rainfall data from FEWSNET were made kindly made available by Benedito Cungara.

identified as terminal or destination markets rather than source markets, while markets located in major maize producing areas are typical source markets. For this reason, impact is also estimated for samples of observations that restrict source markets to typical source markets, destination markets to typical destination markets, or both (see Table1). The spatial price difference is expressed per km to allow full comparison with transport costs by itineraries<sup>14</sup>. Hence, the measure for price dispersion per km is  $y_{jk,t} = (p_{j,t} - p_{k,t})/d_{jk}$  where  $d_{jk}$ =road distance between markets j and k. I have complemented the investigations on price dispersion with investigations on transport costs. Similar to price differences, I express (gross) transport costs between market j and k in period t, per ton and per km. Hence,  $z_{jk,t} = tc_{ijk,t}/(d_{jk}.w_{i,t})$  where  $tc_{ijk,t}$  is gross transport costs for unit i, between market j and k, in period t and  $w_{i,t}$  is unit weight, usually the weight of bags. All values (prices, costs) are deflated with the consumer price index to allow comparisons over time.

I estimate the following difference-in-difference specification, comparing market pairs with and without mobile phone coverage:

$$(1) \quad y_{jk,t} \text{ (or } z_{jk,t}) = \beta_0 + \beta_1 \text{ cell}_{jk,t} + \mathbf{X}_{jk,t} \gamma + \eta_{jk} + \theta_t + \varepsilon_{jk,t}$$

where  $\text{cell}_{jk,t}$  is a binary variable equal to 1 in period t if both markets k and j have mobile phone facilities, and zero otherwise. The vector  $\mathbf{X}_{jk,t}$  represents variables that influence price dispersion and transport costs, such as drought and flooding in sources markets, fuel prices and differences in demand (due to population size and income). Parameters  $\eta_{jk}$  and  $\theta_t$  represent market pair and time fixed effects, and  $\varepsilon_{jk,t}$  is an error term with zero mean and constant variance. The parameter of interest is  $\beta_1$  which measures the per ton per km impact of the introduction mobile phones on either spatial price dispersion or on transport costs.

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<sup>14</sup> Since distance between markets is a fixed effect this transformation is not needed for the estimations.



### *Empirical specification*

With a deflation procedure that is not likely to fully capture price and quality developments and in order to control for technology and network developments, I have included source and destination specific trends to the diff-in-diff specification. Likewise, given the strong seasonality in maize prices, I have also included source and destination specific monthly dummies. Estimations reported in the appendix (see Appendix, Table A2 and A3) confirm that including source and destination specific trends and seasonality clearly improves the performance of the estimation. Covariates ( $X_{jk,t}$ ) are included to control for differences and shocks in demand, supply and trade. In particular I have used the (relative) size of population by city / market to account for differences in demand in source and destination markets. Next, I have included excess and shortage of rainfall as key determinants of supply shocks, in view of the predominantly rain-fed nature of agriculture. Finally, since fuel prices are a major contributor to transport costs, I have included (real) fuel prices interacted with source market dummies as covariate. Drought is specified as the (log) of a threshold rainfall relative to actual rainfall conditional on below threshold rainfall levels, where the threshold rainfall levels refer to a minimum level of seasonal rainfall for agricultural crop output. Values of threshold rainfall levels vary from 600mm to 700mm of total rainfall over the rainy season. In this way the lower seasonal rainfall below the threshold level, the larger the influence of drought, while there is no influence if rainfall is above the threshold level. Flooding is specified as a dummy reflecting the occurrence of rainfall intensities of above 150 to 200mm per decadal (10 days). The influence of rainfall shocks, both drought and flooding, is assumed to extend over the entire subsequent marketing season (from April to March).

#### 4. Empirical Estimation, Heterogeneity and Robustness Checks

##### *Impacts on price dispersion*

Table 1 reports the estimation results of the empirical specification proposed in the methodology section. If I control for market pair fixed effects, year-month fixed effects, seasonality and trends, by source and destination, the first column shows a statistically significant reduction in price dispersion between markets of 228 meticaïs per 1000kg per km<sup>15</sup>. Evaluated at the average of the pre mobile phone price dispersion this indicates that the introduction of mobile phones reduces price dispersion with around 4.5% relative to price dispersion before the introduction of mobile phones.

**Table 1a Impact of mobile phones on dispersion of maize prices: basic specification**

dependent variable: real positive maize price difference between markets, per km ( $(p_{j,t} - p_{k,t})/d_{jk}$ )

	(1)	(2)	(3)	(4)
cell phone dummy	-228*** (85)	-332*** (109)	-459*** (117)	-580*** (141)
trend by source	yes	yes	yes	yes
trend by destination	yes	yes	yes	yes
seasonality by	yes	yes	yes	yes
source (dummies)				
seasonality by	yes	yes	yes	yes
destination (dummies)				
market pairs	yes	yes	yes	yes
(dummies)				
year-month	yes	yes	yes	yes
(dummies)				
Adj R <sup>2</sup>	0.498	0.515	0.491	0.504
No. of observations	39,498	25,568	20,723	13,446

Note to table: Maize price data (source: SIMA) are from January 1999 to December 2007. Nominal series are deflated with the consumer price index, and divided by road distance. Equations are estimated using OLS. Column (1): all data<sup>16</sup>; column (2) is based on a subset of market pairs with typical terminal markets as destination market, column (3) on a subset of pairs with typical production areas as source markets and column (4) combines the restrictions of column (2) and (3). Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Columns (2), (3) and (4) in Table 1 respectively report impact estimations with data restricted to typical destination locations (column (2)), typical source locations (column (3)), and both

<sup>15</sup> Estimations that, additionally, include market pair trends are shown in the appendix (see Table A5). Impacts are of similar size and significance. Since including market pair trends exhausts the degrees of freedom, such a specification cannot be implemented in the transport cost estimations.

<sup>16</sup> Around 3% of the observations at the right tail of the distribution of the dependent variable are dropped.

typical destination and source locations (column (4)). These subsets are justified by the idea that price differences between typical source and typical destination markets are specifically explained by trade costs and efficiency of markets (rather than price difference between either typical source markets mutually, or between typical destination markets mutually). These restriction, for example, skips observations of market pairs that have cities like Maputo, Beira and Xai-Xai as source markets<sup>17</sup>, or market pairs that have cities like Alto Molocue, Montepuez and Gorongosa as destination markets. Both subsets show larger reductions in price dispersion ranging from 332 to 580 meticaïs per 1000kg per km, a reduction of around 6.5%, 9% and 11% relative to price dispersion before the introduction of mobile phones.

#### *Heterogeneity in impacts on price dispersion*

I investigate various sources of heterogeneity in impacts, notably distance between markets, poverty in source markets, the density of the mobile phone network, north and south of Zambezi and drought periods. For this purpose I interact the mobile phone dummy respectively with road distance, poverty head count, mobile phone density<sup>18</sup>, and with market pairs north and south of the Zambezi, and with drought periods. Estimations are reported in Table 1b.

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<sup>17</sup> Alternatively, we may argue that transport costs between typical destination locations is driven by differences in demand, but do not necessarily reflect trade costs associated with maize trade between these destination location.

<sup>18</sup> Cell phone density of each market in each period is calculated as the sum of the cellphone dummy for each market divided by the distance to these markets.

**Table 1b Impact of mobile phones on dispersion of maize prices: heterogeneity**

dependent variable: real positive maize price difference between markets, per km $((p_{i,t} - p_{k,t})/d_{ik})$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
cell phone dummy	-228*** (85)	-181* (105)	-274*** (90.6)	-152* (84)	-321*** (86.9)	-214** (85.9)	-118 <sup>a</sup> (75.9)	-354*** (83)
distance x cell dummy		-94.7 (88.9)						
poverty hc x cell dummy			115* (69)					
cell network x cell dummy				-210*** (80.7)				
north x cell dummy					265 (211)			
south x cell dummy					168 (145)			
drought x cell dummy						-97.4 (86.5)		
lagged dep. variable							0.23*** (0.038)	
joint impact		-275*** (86)	-159* (90.6)	-362*** (103)	-56 <sup>b</sup> (236)	-311*** (111)		
covariates	no	no	no	no	no	no	no	yes
trend by source	yes	yes	yes	yes	yes	yes	yes	yes
trend by destination	yes	yes	yes	yes	yes	yes	yes	yes
seasonality by source (dummies)	yes	yes	yes	yes	yes	yes	yes	yes
seasonality by destination (dummies)	yes	yes	yes	yes	yes	yes	yes	yes
market pairs (dummies)	yes	yes	yes	yes	yes	yes	yes	yes
year-month (dummies)	yes	yes	yes	yes	yes	yes	yes	yes
R <sup>2</sup>	0.498	0.498	0.498	0.498	0.498	0.498	[0.596]	0.503
number of observations	39,498	39,498	39,498	39,498	39,498	39,498	26,098	39,498

Note to table: Maize price data (source: SIMA) are from January 1999 to December 2007. Nominal series are deflated with the consumer price index, and divided by road distance. Distance dummy = 1 if the road distance between markets is larger than 1100km, and 0 otherwise. Poverty head count dummy = 1 if the poverty headcount in source markets is higher than 52%, and 0 otherwise (50<sup>th</sup> percentile). Cell phone network dummy = 1 if the network density index is above 50, and 0 otherwise. Cell phone density index of a source market is the sum of cell phone dummies of neighboring markets divided by the distance to these markets. North (South) dummy = 1 if market pair is north (south) of Zambezi, and 0 otherwise. Covariates include drought and flooding in the districts of the source market, relative population and fuel prices by source markets. Equations are estimated using OLS. Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

a. The long run impact is -154 and is calculated as  $\beta/(1-\rho)$  where  $\rho$  is the coefficient of the lagged dependent variable. b. Joint effect for north of Zambezi.

The estimation results support a stronger impact for market pairs that are farther apart, for market pairs with lower poverty head count at the source market, for market pairs with a higher mobile phone density and for marketing periods after droughts. There is no support for stronger or weaker effects for market pairs either north or south of Zambezi (the evidence

points at a non-significant but slightly stronger impact for market pairs south of Zambezi). Estimation including covariates (flooding and drought, fuel prices and population), reported in column 8, deserve special mention: accuracy of the impact variable improves substantially and increases in size. Especially drought and flooding are both highly significant and negative (!), suggesting that the dispersion between destination and source decreases during these periods. In the aftermath of drought and flooding high prices, apparently prevail in both source and destination markets (unlike the dispersion in normal periods, with high prices limited to destination markets).

### *Impacts on transport costs*

I proceed with estimating the impact of mobile phone introduction on transports costs. These estimation are reported in Table 2a and 2b. Using all available data and controlling for trends and seasonality, the impact is statistically significant at the 1% level (column (1)). Next, and analogous to the estimations on price dispersion, I have either restricted the data to market pairs that have destinations that may be considered well established terminal markets, or (the inverse) that have source markets that may be considered well established source markets<sup>19</sup>. These restrictions increase impact: the introduction of mobile phones has a significant negative impact varying from 563 to 844. Including seasonality, either by source of destination, and (destination specific) trends improves the fit of the estimation substantially.

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<sup>19</sup> To tackle measurement errors in the data, I have, in the first place, verified the nominal values of the transport costs data through regression on determinants, and used this result to identify outliers (see Table A1 in the Appendix).

**Table 2a Impact of mobile phones on transport costs: basic specification**

dependent variable: real transport costs of maize grain per ton-km				
	(1)	(2)	(3)	(4)
cell phone dummy	-563*** (175)	-641*** (167)	-737*** (231)	-844*** (215)
trend by source	yes	yes	yes	yes
trend by destination	yes	yes	yes	yes
seasonality by source (dummies)	yes	yes	yes	yes
seasonality by destination (dummies)	yes	yes	yes	yes
market pairs (dummies)	yes	yes	yes	yes
year-month (dummies)	yes	yes	yes	yes
R <sup>2</sup>	0.839	0.867	0.837	0.868
no. of observations	1142	995	809	712

Note to table: Transport cost data are from August 2001 to December 2010. Nominal series are deflated with the consumer price index, and divided by road distance and bag weight. Equations are estimated using OLS. Column (1): all data<sup>20</sup>; column (2) is based on a subset of market pairs with typical terminal markets as destination market, column (3) on a subset of pairs with typical production areas as source markets and column (4) combines the restrictions of column (2) and (3). Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

The size of the reduction is larger in the case of transport costs than in the case of price differences, where the difference between these impacts ranges from 264 to 335, equivalent to 5% to 6% of average maize prices. Under conditions of trade between markets, the price difference between markets reflects transaction costs. Transaction costs may be decomposed into transport costs, rent extraction and ‘other transaction costs’. If we assume that other transaction costs are not impacted by the introduction of mobile phones, the estimated impacts suggest that, jointly with improved arbitrage between markets, traders have realised increased rent income.

#### *Heterogeneity in impacts on transport costs*

Similar to estimations on price dispersion, I investigate various sources of heterogeneity in impacts, notably distance between markets, poverty in source markets, the density of the mobile phone network, north and south of Zambezi and drought periods. For this purpose I interact the mobile phone dummy respectively with road distance, poverty head counts,

<sup>20</sup> Analogous to the estimations of price dispersion, around 3% of the observations at the right tail of the distribution of the dependent variable are dropped.

mobile phone density above a threshold level, and market pairs respectively north and south of the Zambezi, and drought periods. Estimations are reported in Table 2b. The estimation in Table 2b support larger impacts for markets that are farther apart, for source markets that have lower poverty head counts and for source markets with higher mobile phone density. Outcomes also suggest that impacts are much smaller for market pairs south of the Zambezi, compared to north of the Zambezi. Again, all larger effects are statistically significant at least at the 5% level. With the exception of the *north / south of Zambezi* outcomes, all identified heterogeneity in outcomes is consistent with heterogeneity in the impact in price dispersion. In contrast with the price dispersion estimations, estimation including covariates (flooding and drought, fuel prices and population), reported in column 8, does not improve accuracy of the impact. But again, drought and flooding are both highly significant and negative: an interpretation of these negative coefficients in terms of transport costs is, however, more difficult.

**Table 2b Impact of mobile phones on transport costs: heterogeneity**

dependent variable: real transport costs of maize grain per ton-km								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
cell phone dummy	-563*** (175)	-512** (197)	-577*** (167)	-452** (197)	-785** (382)	-508*** (168)	-588*** <sup>a</sup> (159)	-690*** (229)
distance x cell dummy		-275 (360)						
poverty hc x cell dummy			80 (237)					
cell network x cell dummy				-365 (262)				
north x cell dummy					-50.4 (403)			
south x cell dummy					557 (566)			
drought x cell dummy						-431* (241)		
lagged dep. variable							0.06** (0.036)	
joint impact		-787** (336)	-497* (294)	-817*** (223)	-835*** <sup>b</sup> (223)	-938*** (252)		
Covariates	no	no	no	no	no	no	no	yes
trend by source	yes	yes	yes	yes	yes	yes	yes	yes
trend by destination	yes	yes	yes	yes	yes	yes	yes	yes
seasonality by source	yes	yes	yes	yes	yes	yes	yes	yes

(dummies)								
seasonality by destination	yes	yes	yes	yes	yes	yes	yes	yes
(dummies)								
market pairs	yes	yes	yes	yes	yes	yes	yes	yes
(dummies)								
year-month	yes	yes	yes	yes	yes	yes	yes	yes
(dummies)								
R <sup>2</sup>	0.8387	0.8388	0.8388	0.8395	0.8395	0.8403	[0.836]	0.8443
number of observations	1142	1142	1142	1142	1142	1142	1047	1142

Note to table: Transport cost data are from August 2001 to December 2010. Nominal series are deflated with the consumer price index, and divided by road distance and bag weight. Distance dummy = 1 if the road distance between markets is larger than 940km, and 0 otherwise (66.6<sup>th</sup> percentile). Poverty head count dummy = 1 if the poverty headcount in source markets is higher than 55%, and 0 otherwise (66.6<sup>th</sup> percentile). Cell phone network dummy = 1 if the network density index is above 54, and 0 otherwise (66.6<sup>th</sup> percentile). Cell phone density index of a source market is the sum of cell phone dummies of neighboring markets divided by the distance to these markets. North (south) dummy = 1 if market pair is north (south) of Zambezi, and 0 otherwise. Covariates include drought and flooding in the districts of the source market, relative population and fuel prices by source markets. Equations are estimated using OLS. Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

a. The long run impact is -628 and is calculated as  $\beta/(1-\rho)$  where  $\rho$  is the coefficient of the lagged dependent variable. b. Joint effect for north of Zambezi.

### *Robustness checks: equality of pre-intervention trends of treated and non-treated*

The diff-in-diff approach requires that that pre-intervention outcomes of intervention and control groups have a common trend. Since all market-pairs obtain access to mobile phone facilities in the course of the rollout, there is no strict distinction between intervention and control groups. However, it is possible to test the common trend assumption in the pre-intervention period for market pairs that obtain access in year  $t$ , with market pairs that obtain access only in year  $t+k$ . For example, for market pairs obtaining access in 2003 I test if the trend for the years 1999 to 2002 is different from the trend (for the same period) of market pairs obtaining access only in 2004 or later. I have tested if the estimated coefficients of trends for treated and not (yet) treated differ, using a standard F-test. Results are reported in Table 3a and 3b. On the basis of the test results I cannot reject the hypothesis of a common trend in the pre-treatment period for treated and not treated, and for both price dispersion and transport costs<sup>21</sup>.

<sup>21</sup> For three price dispersion test outcomes (estimation (1), 2005; (2), 2005 and (3), 2006) equality is rejected at the 5% level. In the course of the rollout, the balance of the observations is skewing towards the treated group,



**Table 3a Testing equality of pre-treatment trends in dispersion of maize prices**dependent variable: real positive maize price difference between markets, per km ( $(p_{i,t} - p_{k,t})/d_{ik}$ )

smpl <sup>a</sup>	(1)				(2)				(3)			
	treated	non treated	F() F p>F	# obs	treated	non treated	F() F p>F	# obs	treated	non treated	F() F p>F	# obs
2001	65.4 (44)	19.0 (33.4)	1;495 1.51 (0.22)	8997	52.4 (44)	54.4 (21)	1;258 0.00 (0.97)	5258	102 (35)	46.4 (15)	1;278 2.08 (0.15)	6299
2002	-20.2 (12)	-45.8 (15)	1;516 3.24 (0.07)	12761	-15.8 (17)	-48.5 (20)	1;265 2.77 (0.10)	7555	-22.0 (17)	-45.9 (19)	1;287 1.70 (0.19)	8682
2003	-6.7 (5.5)	-7.9 (5.8)	1;538 0.06 (0.81)	15575	-21.1 (7.4)	-17.3 (7.6)	1;281 0.28 (0.60)	9118	-9.6 (8.2)	-18.3 (7.8)	1;297 1.85 (0.17)	10419
2004	-5.2 (4.6)	2.6 (4.8)	1;552 1.97 (0.16)	19492	-3.1 (6.0)	6.7 (6.4)	1;294 2.06 (0.15)	11975	-6.7 (5.3)	-1.7 (5.7)	1;298 0.61 (0.43)	12886
2005	2.1 (3.3)	11.9 (4.0)	1;559 4.07 (0.04)	24007	2.5 (3.6)	15.7 (4.8)	1;297 5.58 (0.02)	15463	0.6 (4.4)	7.1 (4.3)	1;298 1.23 (0.27)	15709
2006	4.0 (3.7)	10.8 (4.0)	1;592 1.82 (0.18)	28711	3.3 (7.6)	10.0 (4.4)	1;322 0.66 (0.42)	18912	-1.5 (3.9)	8.4 (4.2)	1;306 4.03 (0.05)	18295

Note to table: Maize price data (source: SIMA) are from January 1999 to December 2007. Nominal series are deflated with the consumer price index, and divided by road distance. Equations are estimated using OLS. All estimations include month x year and market pair dummies, seasonality by source and destination, and trends by source, destination and market pair. Column (1): all data; column (2) is based on a subset of market pairs that excludes typical producer areas / assembly markets as destination market, while column (3) is based on a subset of pairs that excludes typical terminal markets as source markets (see also Table 1a). *Treated* (*non-treated*) is a trend variable for the pre-treatment period (up to t-1) for market pairs that obtained access to mobile phones in year t (*treated*) and for those that do not (yet) have access (*non-treated*) in year t. F is F-test of  $\text{coef}(\text{treated}) = \text{coef}(\text{non-treated})$  with p values in brackets below the F statistic. Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

a. The sample period is characterized by the year of introduction of mobile phones: if this is, for example, 2004, the pre-intervention sample is restricted to the period 1999-2003 (1999 is the first year of price data).

**Table 3b Testing equality of pre-treatment trends in transport costs**

dependent variable: real transport costs of maize grain per ton-km

smpl <sup>a</sup>	(1)				(2)				(3)			
	treated	non treated	F() F p>F	#obs	treated	non treated	F() F p>F	#obs.	treated	non treated	F() F p>F	#obs
2003	89.6 (178)	67.2 (12)	1; 61 0.02 (0.90)	378	94.6 (158)	66.8 (19)	1; 51 0.03 (0.86)	322	168.1 (5.4)	169.1 (10.0)	1; 29 0.04 (0.85)	202
2004	-42.5 (9 2)	24.2 (19)	1; 83 0.49 (0.49)	638	-28.9 (93)	29.2 (27)	1; 70 0.35 (0.55)	548	-77.0 (96.4)	53.9 (95.2)	1; 43 0.56 (0.46)	386
2005	15.2 (17)	-43.0 (69)	1; 85 0.72 (0.40)	707	13.1 (22)	48.6 (95)	1; 72 0.14 (0.71)	617	22.6 (28)	59.3 (111)	1; 44 0.11 (0.74)	435

Note to table: Transport cost data are from August 2001 to December 2010. Nominal series are deflated with the consumer price index, and divided by road distance and bag weight. Equations are estimated using OLS. All

easily leading to different (and statistically significant) trends for a small non-treated group. Hence, this should not be a major concern.

estimations include month x year and market pair dummies, seasonality by source and destination, and trends by source and destination. Column (1): all data; column (2) is based on a subset of market pairs with typical terminal markets as destination market, while column (3) is based on a subset of pairs with typical production areas as source markets (see also Table 2a). *Treated* (*non-treated*) is a trend variable for the pre-treatment period (up to t-1) for market pairs that obtained access to mobile phones in year t (*treated*) and for those that do not (yet) have access (*non-treated*) in year t. F is F-test of  $\text{coef}(\textit{treated}) = \text{coef}(\textit{non-treated})$  with p values in brackets below the F statistic. Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

a. The sample period is characterized by the year of introduction of mobile phones: if this is, for example, 2004, the pre-intervention sample is restricted to the period 2001-2003 (2001 is the first year of transport costs data).

### *Robustness checks: impacts with propensity score matching estimations*

In order to address possible selection bias, I proceed with estimating the impacts using propensity score matching, a powerful and well established technique for non-experimental data to address these issues. The propensity score (i.e. the probability of treatment, hence, in this analysis the probability to have access to mobile phone technology), estimated with a logit model since the treatment is binary, uses the following covariates (X)<sup>22</sup>: a trend variable, interactions of year dummies with distance between markets and with (the sum of) population in source and destination markets. Both latter variables are associated with the attractiveness to install mobile phone technology. These variables simultaneously influence assignment into treatment or control group and the outcome variable in both price dispersion and transport costs, and are themselves unaffected by assignment into treatment / control. Coefficients of the covariates in the propensity score estimation have expected signs: positive for population and declining over the years, and negative in the first years for distance between markets. In order to match treatment and control observations, I use nearest neighbour matching using 3 to 10 of the nearest controls combined with a caliper threshold. Estimations are dependent on the ordering of the data and hence Table 4a and 4b report a specific (though reasonably representative) outcome. The overlap and region of common support between treatment and comparison group is shown graphically in the appendix (see

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<sup>22</sup> I experimented with a larger set of covariates including distance to Maputo, average poverty head count in source and destination markets, road quality, both independently and interacted with year dummies, and trends by source and destination.

Appendix, Figure A8). In the case of price dispersion, the propensity score distribution before matching is very different in the treatment and the control group: in the control group the propensity score is highly skewed towards the lower end and in the treatment group to the higher end, largely due to the increase in treatment over time. A satisfactory common support (by matching in such a way that a closely resembling distribution of the propensity score is realised) is difficult to find (see also common support figures in Appendix). Testing the matching quality, for example by estimating the equality of the means of covariates in treatment and control group after matching is therefore also omitted. In the case of transport costs the common support after matching is much more satisfactory (see Appendix).

**Table 4a Impact of mobile phones on dispersion of maize prices: PSM estimation**

dependent variable: real positive maize price difference between markets, per km ( $(p_{i,t} - p_{k,t})/d_{ik}$ )			
	(1)	(5')	(9')
ATT	-420.0*** (62.9)	-497.5*** (96.9)	-541.9*** (71.9)
no. of observations	28,711	19,097	14,417

Note to table: Maize price data (source: SIMA) are from January 1999 to December 2007. Nominal series are deflated with the consumer price index, and divided by road distance. Equations are estimated using Propensity Score Matching (see main text for details). Column (1): all data; (5') is based on a subset of market pairs that excludes typical producer areas / assembly markets as destination market, while column (9') is based on a subset of pairs that excludes typical terminal markets as source markets. Standard errors are in brackets below the coefficient. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

**Table 4b Impact of mobile phones on transport costs: PSM estimation**

dependent variable: real transport costs of maize grain per ton-km			
	(1)	(5')	(9')
ATT	-717.7** (340)	-665.7** (304)	-846.4 (639)
no. of observations	568	481	386

Note to table: Transport cost data are from August 2001 to December 2010. Nominal series are deflated with the consumer price index, and divided by road distance and bag weight. Equations are estimated using Propensity Score Matching (see main text for details). Column (1): all data; column (5') is based on a subset of market pairs with typical terminal markets as destination market, while column (9') is based on a subset of pairs with typical production areas as source markets. Standard errors are in brackets below the coefficient. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Despite the not entirely satisfactory properties of the propensity score matching, the PSM impact estimations by and large confirm the results obtained through OLS / diff-in-diff. If

anything, the results suggest an impact on price dispersion that is at the high end of the ordinary OLS / diff-in-diff estimates (see Table 1a), and this also applies to the PSM estimated impact on transport costs (see Table 2a). Estimated PSM impacts are also higher in transport costs relative to price dispersion.

## **5. Discussion of outcomes, summary and conclusion**

This study investigates empirically the impact of the mobile phone roll-out in Mozambique on price dispersion and transport costs. Estimations suggest a 4.5% to 11% decrease in price dispersion. This evidence supports an improvement in the efficiency of maize markets as a result of the introduction of mobile phones. The reduction in transport cost is larger: for different specifications this reduction is 265 to 335 meticaís larger, evaluated at the average maize price this corresponds with a 5% to 6% larger reduction. The larger impact on trade costs suggests that a part of the benefits of the introduction of mobile phones translates into increased rents for traders, apart from an improved arbitrage and efficiency of maize markets. Impacts are shown to be heterogeneous in various ways: the reduction in price dispersion and transport costs is larger for markets that are more remote, for source markets with a lower poverty head count, for source markets with a higher density of the mobile phone network and during drought periods. The results do not unambiguously indicate a different impact north of the Zambezi compared to south of the Zambezi. Robustness of these results is verified by checking the parallel trend assumption underlying the diff-in-diff approach, and by employing propensity score matching to control for possible selection bias.

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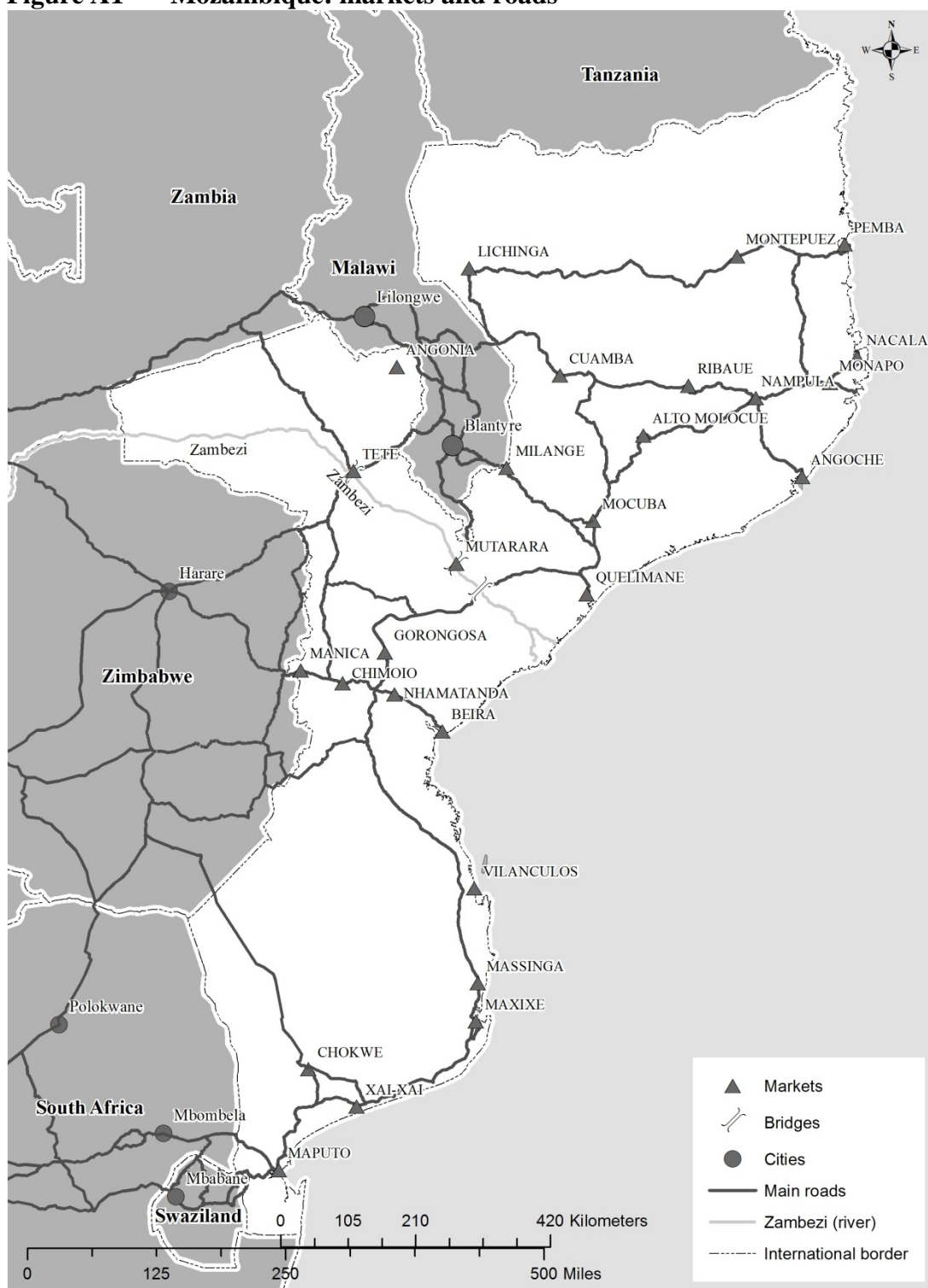
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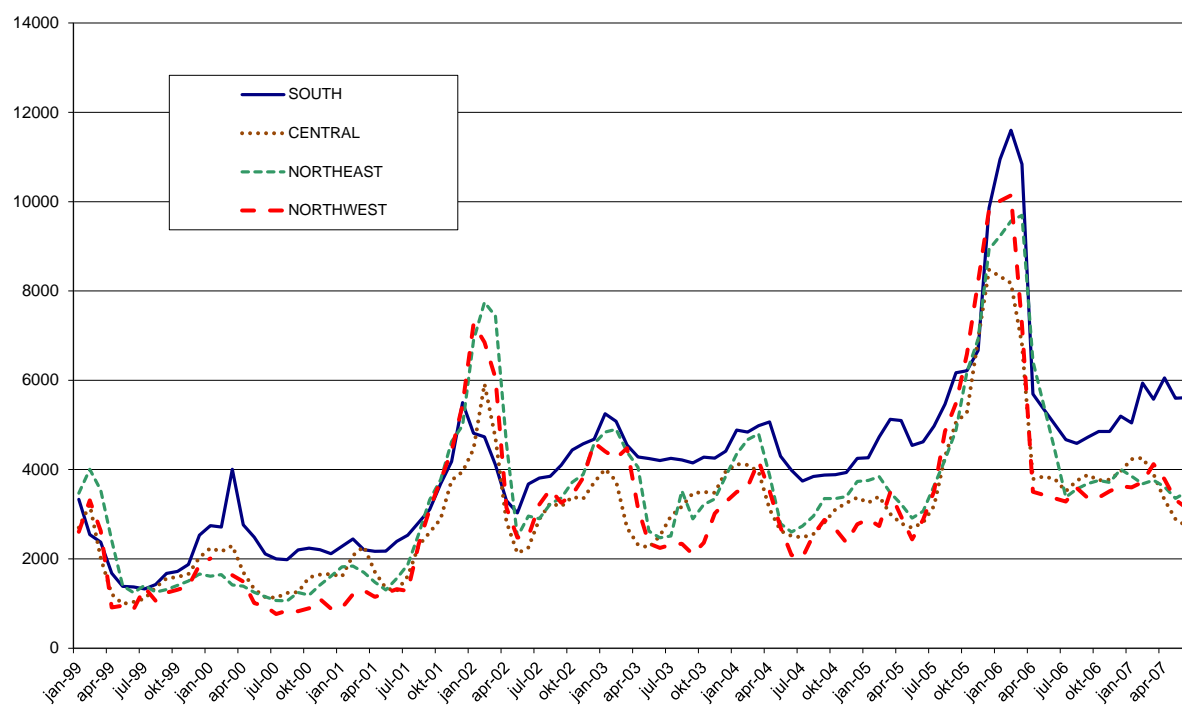
## Appendix

**Figure A1 Mozambique: markets and roads**



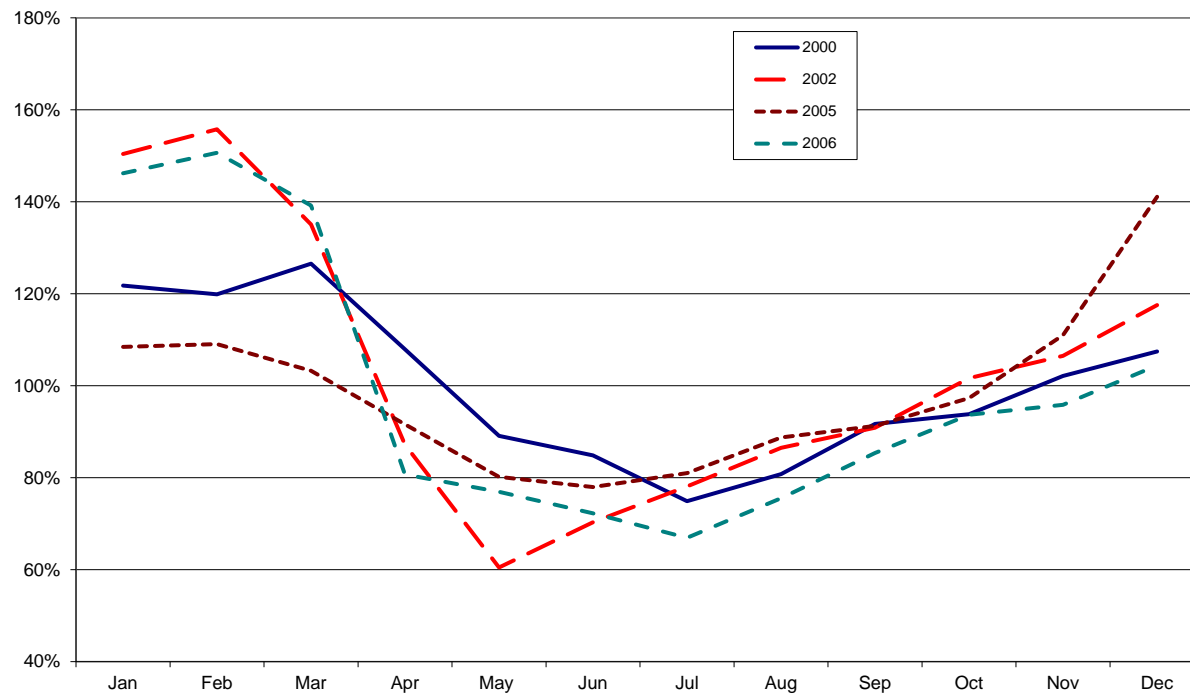


**Figure A2 Maize price by region (nominal prices, January 1999-July 2007)**



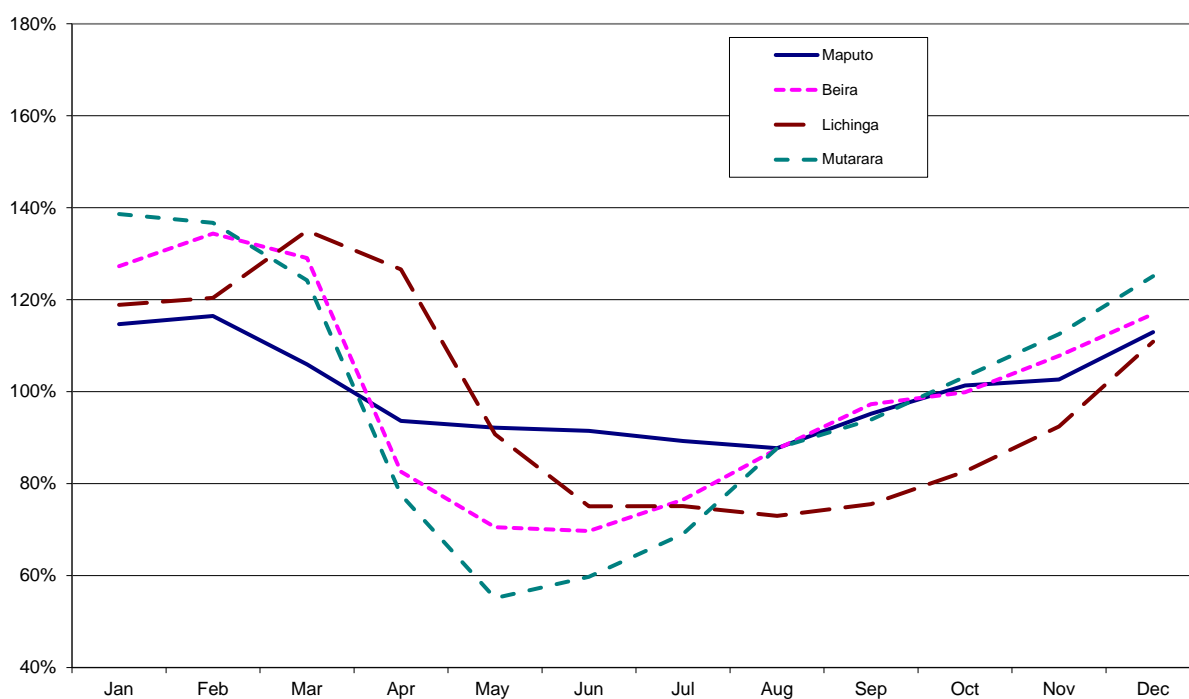
Source: SIMA

**Figure A3 Seasonality in maize prices, by year, selected years**



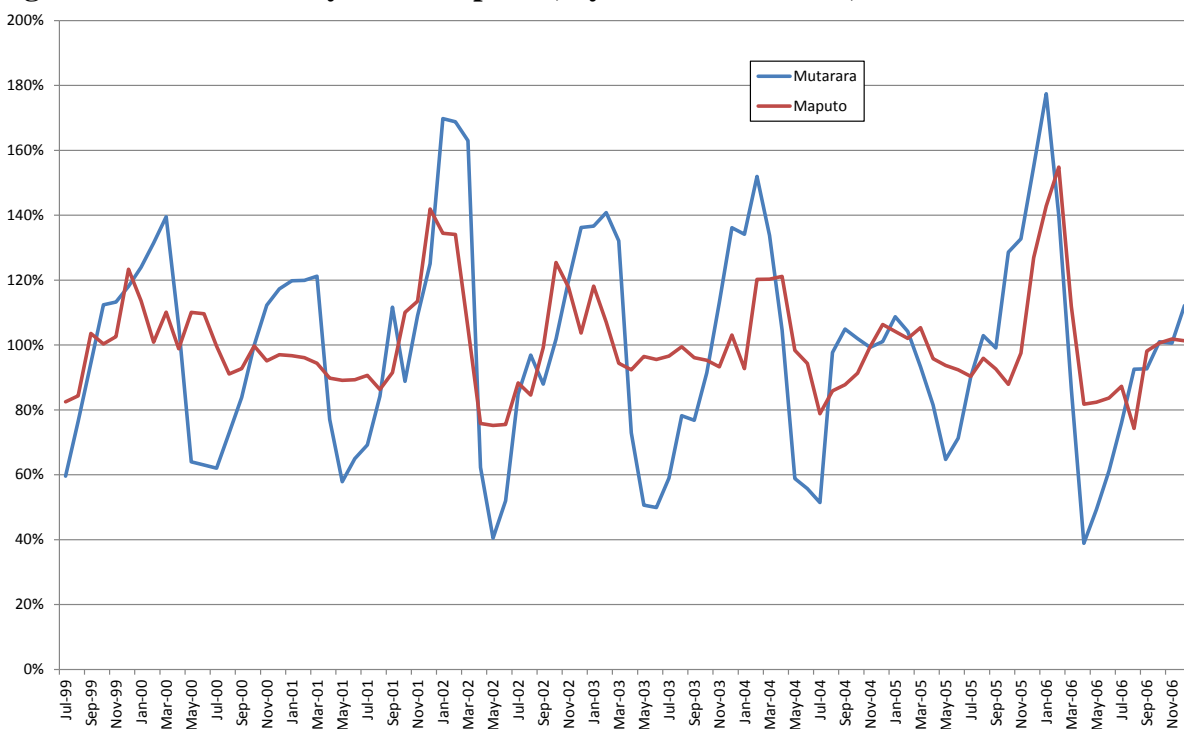
Source: (author's calculations based on) SIMA

**Figure A4 Seasonality in maize prices, by market, selected markets**



Source: (author's calculations based on) SIMA

**Figure A5 Seasonality in maize prices, by market over time, source and destination**



Source: (author's calculations based on) SIMA

**Table A1 Using determinants of transport costs to verify and clean the data**

dependent variable: nominal transport costs for bags of maize grain, different sources and destination markets				
	(1)	(2)	(3)	(4)
road distance	86.2*** (5.1)	77.5*** (5.2)	106.0 (74.2)	
road quality	-941.5*** (164.8)	-830.5*** (165.4)	-1060.8 (1926)	
fuel price	3337.0*** (642.9)	yes <sup>a</sup>	yes <sup>a</sup>	3236.5*** (1014.3)
weight of bags	282.0*** (64.8)	265.0*** (64.3)	283.6*** (62.5)	307.4*** (62.6)
consumer price index	3757.2*** (1195.3)	3583.1*** (1179.5)	3110.6*** (1114.2)	3421.2*** (1461.0)
Trend	-2349.7*** (700.5)	-2102.8*** (691.0)	-1830.5*** (650.7)	-2126.1** (927.4)
market pairs (dummies)	no	no	yes	yes
seasonality by source market (dummies)	yes	yes	yes	yes
seasonality by destination market (dummies)	yes	yes	yes	yes
year (dummies)	yes	yes	yes	yes
R <sup>2</sup>	0.714	0.732	0.792	0.784
sample period	8-01/12-10	8-01/12-10	8-01/12-10	8-01/12-10
number of observations	1187	1187	1187	1187

Note to table: Road quality is defined as road distance in kilometers per hour traveling time. Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

a. Fuel price interacted with source market.

**Table A2 Price differences and transport costs over the years, selected itineraries**

Average price dispersion for selected itineraries														
itinerary	year												pre	post
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010		
Chimoio – Beira	3008	1899	2315	1511	2904	2600	5191	3617	4118				3008	3241
Chimoio – XaiXai	1530	2845	1760	1058	2493	1249	1328	2115	2528				2060	1826
Lichinga – Nacala	1251	1045	1618	1451	2791	2302	2633	1872	1869				1256	2269
Cuamba – Beira	1171	2563	573		1069	1079	1247	1558	1080				1244	1180
Tete – Maputo	1652	3183	2314	1741	2710	2384	1712	2121	2343				2395	2222
Nampula – Beira	1248	1708	1836	231	611	394	852	912	706				1521	987
Average transport costs for selected itineraries														
itinerary	year												pre	post
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010		
Monapo – Nacala				1989	2313	2244	3788	3261	1676	1540	3105		4681	2299
AltoMolocue – Nampula				4503	4242	3854	3539	4169	4191	3890	3721	3128	4372	3746
AltoMolocue – Quelimane			2624	3424	3955	3611	3543	3166	4317	4542	3385	2931	3892	3556
AltoMolocue – Maputo				1638	2070		1188		1073		799		1818	999
Angonia – Tete			2330	3679	3939		4525	3183	3560	2998	3247	2326	3797	4016
Chimoio – XaiXai			1671	1318	978	2394	2180	1191	2069				1671	1464

**Table A3 Impact of mobile phones on dispersion of maize prices: including source and destination specific trends and seasonality to the basic specification**

dependent variable: real positive maize price difference between markets, per km ( $(p_{i,t} - p_{k,t})/d_{ik}$ )									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
cell phone dummy	-228*** (85)	-109.8 (82.0)	-148* (82.7)	-95.5 (87.4)	-135.1 (87.6)	-112.4 (84.4)	-151* (83.7)	-153* (84.8)	-191** (86.3)
trend by source	yes	yes	no	no	no	yes	yes	no	no
trend by destination	yes	no	yes	no	no	no	no	yes	yes
seasonality by source (dummies)	yes	no	no	yes	no	yes	no	yes	no
seasonality by destination (dummies)	yes	no	no	no	yes	no	yes	no	yes
market pairs (dummies)	yes	yes	yes	yes	yes	yes	yes	yes	yes
year-month (dummies)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj R <sup>2</sup>	0.498	0.436	0.447	0.443	0.463	0.448	0.468	0.460	0.478
No. of observations	39,498	39,498	39,498	39,498	39,498	39,498	39,498	39,498	39,498

Note to table: Maize price data (source: SIMA) are from January 1999 to December 2007. Nominal series are deflated with the consumer price index, and divided by road distance. Equations are estimated using OLS. Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

**Table A4 Impact of mobile phones on transport costs: including source and destination specific trends and seasonality to the basic specification**

dependent variable: real transport costs of maize grain per ton-km									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
cell phone dummy	-563*** (175)	-381* (217)	-322* (182)	-91.1 (158)	-170 (169)	-296 (185)	-451** (183)	-269 (168)	-348** (174)
trend by source	yes	yes	no	no	no	yes	yes	no	no
trend by destination	yes	no	yes	no	no	no	no	yes	yes
seasonality by source (dummies)	yes	no	no	yes	no	yes	no	yes	no
seasonality by destination (dummies)	yes	no	no	no	yes	no	yes	no	yes
market pairs (dummies)	yes	yes	yes	yes	yes	yes	yes	yes	yes
year-month (dummies)	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj R <sup>2</sup>	0.839	0.756	0.758	0.790	0.789	0.798	0.801	0.803	0.804
No. of observations	1142	1142	1142	1142	1142	1142	1142	1142	1142

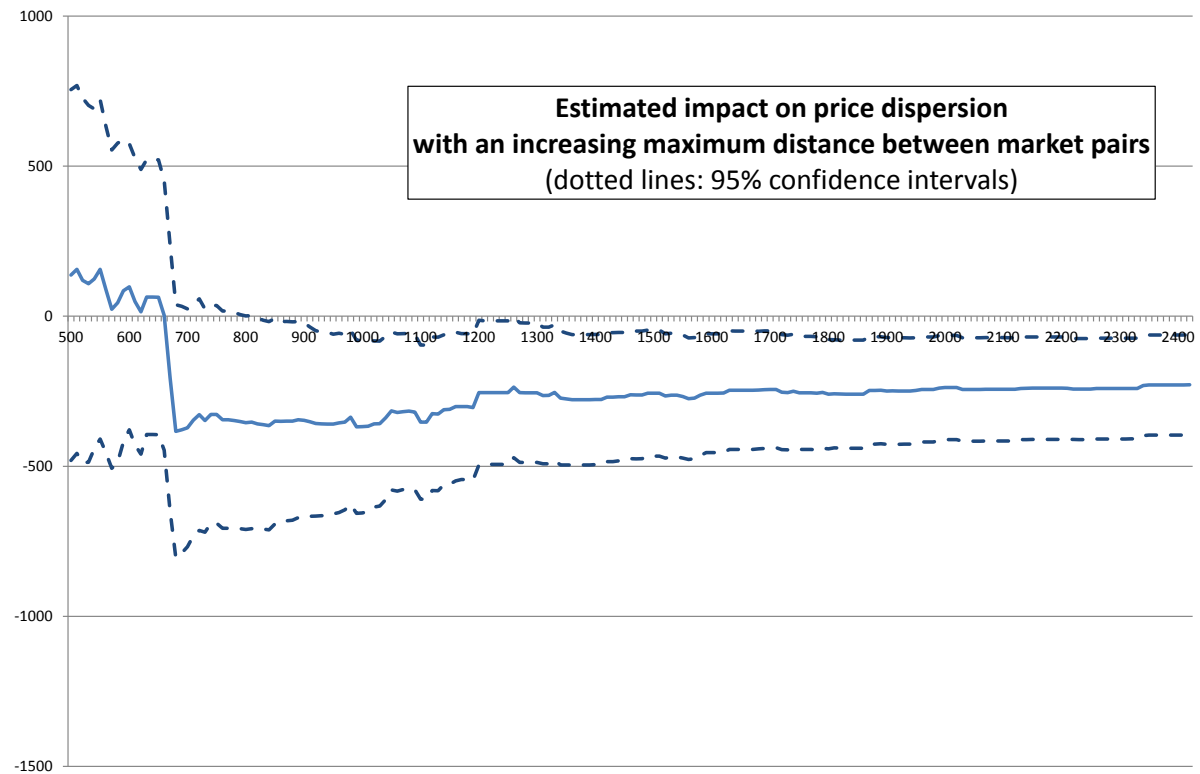
Note to table: Transport cost data are from August 2001 to December 2010. Nominal series are deflated with the consumer price index, and divided by road distance and bag weight. Equations are estimated using OLS. Robust standard errors in brackets below the coefficient are clustered by market-pairs. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

**Table A5 Impact of mobile phones on dispersion of maize prices:  
including market pair trends**

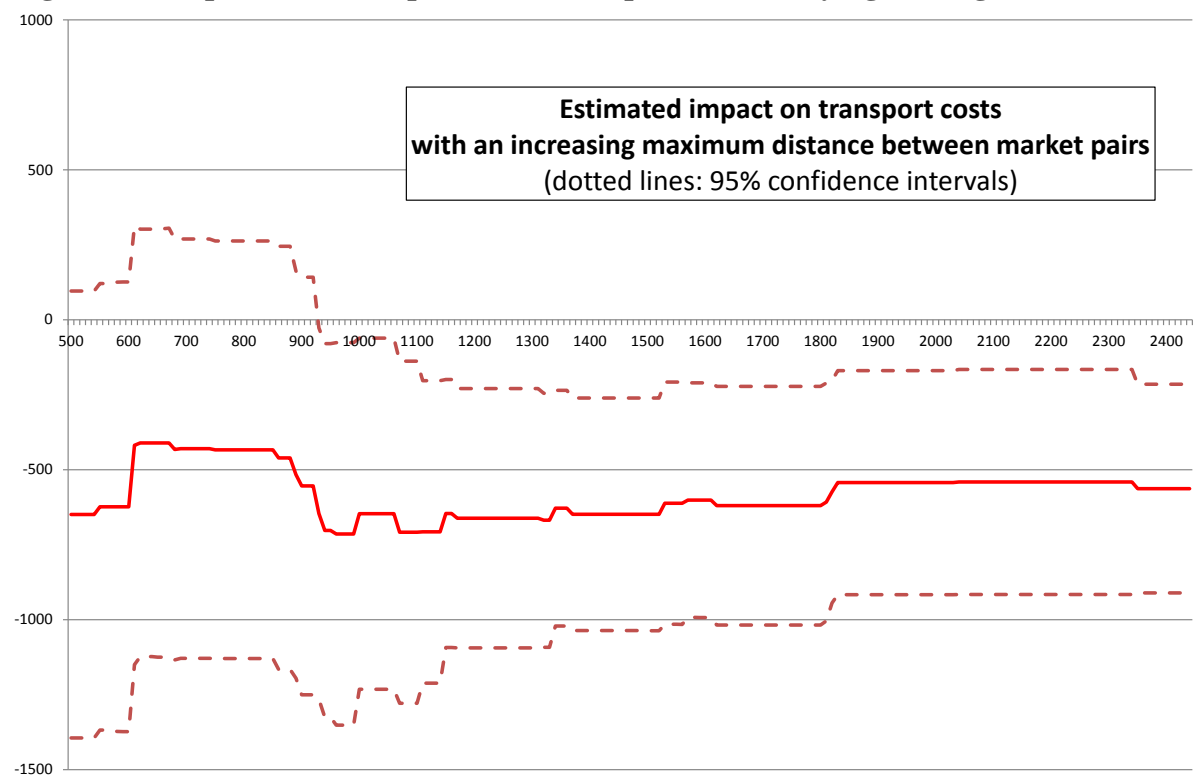
dependent variable: real positive maize price difference between markets, per km $((p_{i,t} - p_{k,t})/d_{jk})$				
	(1)	(2)	(3)	(4)
cell phone dummy	-221*** (89.6)	-310*** (113)	-471*** (126)	-570*** (139)
trend by source	yes	yes	yes	yes
trend by destination	yes	yes	yes	yes
<b>trend by market pair</b>	<b>yes</b>	<b>yes</b>	<b>yes</b>	<b>yes</b>
seasonality by source (dummies)	yes	yes	yes	yes
seasonality by destination (dummies)	yes	yes	yes	yes
market pairs (dummies)	yes	yes	yes	yes
year-month (dummies)	yes	yes	yes	yes
Adj R <sup>2</sup>	0.512	0.526	0.509	0.517
No. of observations	39,498	25,568	20,723	13,446

Note to table: Maize price data (source: SIMA) are from January 1999 to December 2007. Nominal series are deflated with the consumer price index, and divided by road distance. Equations are estimated using OLS. Column (1): all data; column (2) is based on a subset of market pairs with typical terminal markets as destination market, column (3) on a subset of pairs with typical production areas as source markets and column (4) combines the restrictions of column (2) and (3). Robust standard errors in brackets below the coefficient are clustered by market-pairs.  $*p < 0.10$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

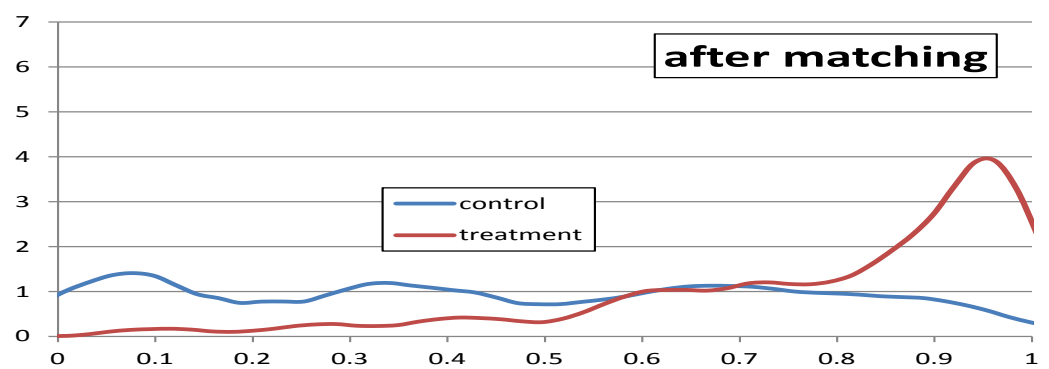
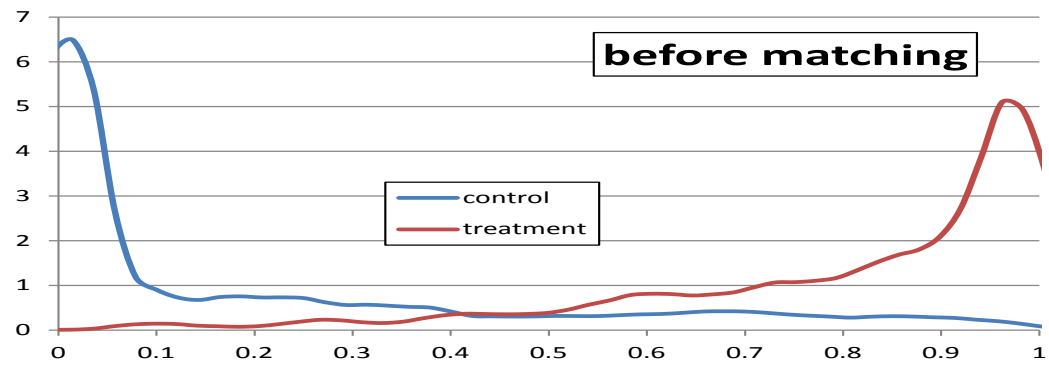
**Figure A6 Impact of mobile phones on dispersion of maize prices: varying trading distance**



**Figure A7 Impact of mobile phones on transport costs: varying trading distance**



**Figure A8** Common support between treatment and control group  
price dispersion



transport costs

