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Mobile Phones and Mozambique Traders: Size, Composition and Distribution of Reduced Transaction Costs

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ABSTRACT

I use unique transport cost data along with spatial market prices to measure the size, composition and distribution of reduced transactions costs due to the roll-out of the mobile phone network in Mozambique. My estimations are based on weekly transport costs of maize grain and weekly maize market prices. The mobile phone roll-out explains a 9%-15% reduction in the spatial price dispersion of maize. The evidence suggests that 70% to 80% comes from lower transport costs. Traders use mobile phones for multiple alternative purposes which explains the large contribution of transport costs. The evidence also indicates that the reduction in spatial price dispersion corresponds with a relatively large drop in destination markets' prices: the benefits of mobile phones appear to accrue mainly to urban consumer markets and much less to producer areas. My results are robust for the non-random roll-out of the mobile phone network and several other threats, and align with evidence found elsewhere in the literature.

1. Introduction

Information, especially price information, is a major requirement for the efficient operation of agricultural markets. The introduction of mobile phones in the late 1990s in Mozambique drastically changed access to information. In a competitive market information about prices in many distant markets, instantaneously and cheaply, will reduce transaction costs and price dispersion across markets. However, mobile phones do not only provide better information about prices. They also provide better information on credit and funding, on freight collection and backhaul cargo, on conditions and accessibility of roads, on weather, on prices and availability of fuel, on repair and maintenance of trucks, on insurance, on road tolls and police checkpoints and on other transport logistics. Transport costs, the largest part of transaction costs, are therefore likely to decrease and potentially affect scale and scope of operation, and competitiveness in trading. While most studies find that mobile phones reduce search costs, there is little information about how mobile phones affect transport costs, how reduced transport costs affect price dispersion across markets, and on the distribution of reduced price dispersion across markets. This paper empirically measures the impact of mobile phones in Mozambique on the spatial dispersion of maize prices and on maize transport costs, examines the relative size of the reduction in transport costs vis-à-vis total transaction costs, and explores the distribution of reduced transaction costs between source and destination markets. My empirical estimates are based on weekly maize market prices and maize transport costs, for 27 markets in Mozambique, from 1999 to 2007, combined with annual data on the rollout of the mobile phone network.

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 (Overa, 2006; Jensen, 2007; Muto and Yamano, 2009; Aker, 2010; Fafchamps and Minten, 2012; Aker and Fafchamps, 2014; Allen, 2014; Tadesse and Bahiigwa, 2015; Aker and Ksoll, 2016). Many of these papers exploit the roll-out of mobile phone infrastructure as an identification strategy. The introduction of mobile phones is shown to have decreased spatial price dispersion and increased market efficiency (Jensen, 2007; Aker, 2010; Aker and Fafchamps, 2014). However, there is less of a consensus on if and how farmers, traders and consumers are affected, what mechanisms explain the impacts of mobile phones, or how the benefits from access to mobile phones are distributed. Some work finds increases in producer profits and consumer welfare, and less waste (Overa, 2006; Jensen, 2007; Muto and Yamano, 2009) and increased market participation (Muto and Yamano, 2009). Allen (2014) finds that more than half of observed price dispersion

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(normally ascribed to transport costs) is due to information frictions which are claimed to be an important determinant of trade flows. Others studies, however, find no impact on farmers' crop choices cultivation practices, marketing, or received prices (Muto and Yamano, 2009, Fafchamps and Minten, 2012; Aker and Fafchamps, 2014). Asymmetric information between traders and farmers, or a comparative advantage in transport is suggested as an explanation for why benefits accrue to traders and not to producers (Muto and Yamano, 2009; Fafchamps and Minten, 2012).

The limited benefits for farmers, combined with larger benefits for traders suggests several explanations. One of these explanations is that mobile phones offer a spectrum of improved information that is broader for traders and particularly helpful in the trading business. Mobile phones increase efficiency in logistics, transport and freight management. They also improve payment technology and increase access to finance. Economies of scale and scope are potential complementary channels that explain why traders benefit more from mobile phones than farmers. Finally, cost reductions and high mark-ups attract new entrants in trade that will change competitiveness in the trading sector.

This paper contributes to this literature in several ways. I first replicate existing estimates of the impact of mobile phones on spatial price dispersion for Mozambique, using prices for maize, a crop that is widely traded and key to food security. Similar to previous work I show that spatial price differences decrease when mobile phones become available. Next, and unlike previous work, I estimate the impact of mobile phones on transport costs, exploiting unique transport cost data, and I compare the impacts on spatial price dispersion and transport costs. Also unlike previous work, I investigate to what extent increased market efficiency leads to price changes in source markets and in destination markets, thereby quantifying to what extent benefits of improved market efficiency accrue to the producer markets or consumer markets. The introduction of mobile phones in Mozambique has reduced maize price dispersion by 9 %-15 %. A large share of this reduction – between 70 % and 80 % – consists of a reduction in transport costs. Finally, the evidence suggests that the benefits of increased efficiency of maize markets are nearly completely captured by consumer markets.

This paper is organized as follows. In Section 2 I describe the Mozambique maize trade and the mobile phone roll-out. In Section 3 I propose a simple conceptual framework. In Section 4 I document my data sources and discuss the samples I used in the estimation procedure. In Section 5 I formulate my empirical strategy. In Section 6 I present my estimates, followed by potential threats, and measurements of the distribution of benefits. I summarize my results in Section 7.

2. Mozambique maize production, trade and prices, and mobile phone roll-out

2.1. Maize production and trade

Maize is the most important staple food of Mozambique: it is widely produced, marketed, exported and consumed. Two thirds of all rural households produce maize, maize is three times more marketed than cassava and households spend about as much on maize as on all other staple foods combined (Tschirley et al., 2006). My empirical work is therefore based on maize prices and maize transport costs. Most agricultural production in Mozambique is rain-fed: because there is more rainfall, a better rainfall distribution, better soil fertility and fewer pests in the central and northern provinces (Abdula, 2005; Figure A7), domestic maize production is concentrated in these parts of Mozambique. Due to widespread subsistence farming only around 30 % of total maize production is actually traded on the market. Niassa, Tete and Manica are the provinces with the largest maize surpluses (Figure A7). Manica, Chimoio and Gorongosa are major production, assembly and wholesale regions in central Mozambique, and Alto Molocue, Montepuez, Mocuba and Ribaue are similarly important regions in the north. The major deficit markets, nearly all along the coast, are Maputo, Xai-xai, Maxixe, Massinga, Beira, Nacala and Pemba (Figure 1).

Trade in white maize grain – the standard maize quality – takes place throughout Mozambique.[1] The Zambezi river which is a natural barrier to domestic trade (Figure 1), has directed major maize trade flows in the past from the central area to the south, south of the Zambezi, and from west to east, north of the Zambezi.[2] Southern Mozambique, 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 primarily sourced from Chimoio or Manica in the central region, around 1100 km away by road (Abdula, 2005; SIMA data from 1999 to 2001), but also from more distant markets.[3] Southern Mozambique, and the Maputo-Matola area in particular, also rely on South Africa as a supplier of maize (Haggblade et al., 2008; FAO, 2014). Maize is exported to Malawi from areas and markets close to Malawi, like Angonia, Cuamba and Milange (USGS / FEWS NET; FAO, 2014). Transport cost data support these stylized facts (Tables A4 and A5).

The key intermediaries in Mozambique long distance maize trade are traders – mostly informal itinerant traders but also large scale assemblers – and transporters (FAO, 2014; De Vletter and Polana, 2001). Itinerant long distance traders are known to make several trips per season (De Vletter and Polana, 2001). Barriers to enter the trading business appear to be low. However, it is likely that working capital is a constraint on business, similar to other sub-Sahara countries (Fafchamps et al. 2005). To my knowledge there is no information on trade flows of maize or on the number of traders involved in maize trade in Mozambique.

Maize transport in Mozambique mainly occurs along a modest road network (Dominguez-Torres and Briceño-Garmendia, 2011). Road network density (km road per 1000 km2 land area) is 29 (classified roads) and 37 (all roads), which is extremely low, even for low income countries. Since the early 1990s the percentage of roads in good or fair condition has increased from 30 % to 83 %, which is above the average of other sub-Saharan low-income countries. Improvements to the trunk roads over the past decades indicate that trunk road quality is not a major impediment to domestic long-distance trade. Note, however, that the relatively good condition of Mozambique's primary network stands in sharp contrast with the condition of the rural network: secondary, tertiary and rural feeder roads are in poor condition. During the rainy season many of these roads are not usable.[4]

2.2. Maize prices

Occasional extreme weather like drought and flooding causes severe

[1] White maize grain is produced, consumed and traded throughout Mozambique and the dominant type of maize: it is safe to assume that white maize grain is a homogenous product throughout Mozambique and over time.

[2] Since 2009 two additional Zambezi bridges are operational: Chimuara-Caia, and Vila de Sena-Mutarara. The Chimuara-Caia bridge was newly built and is part of the main north–south highway. During the period of study, (prior to 2009) the Tete bridge was the only fully operational road bridge on a major highway connection. The north–south barrier to transport has affected maize markets north and south of Zambezi (Zant, 2022).

[3] Maize is also sourced from Tete (Tostão and Wade Brorsen, 2005, using SIMA trade flow data from 1998 to 2001). From Tete to Maputo is around 1500km by road. The longest observed trade route is around 2300km by road (Lichinga-Maputo).

[4] Accessibility to rural areas is very low: although 70% of the population is living in rural areas and 22% of Mozambique's GDP originates from agriculture, only around 25% of rural Mozambicans live within 2 km of a classified network road (Dominguez-Torres and Briceño-Garmendia, 2011).

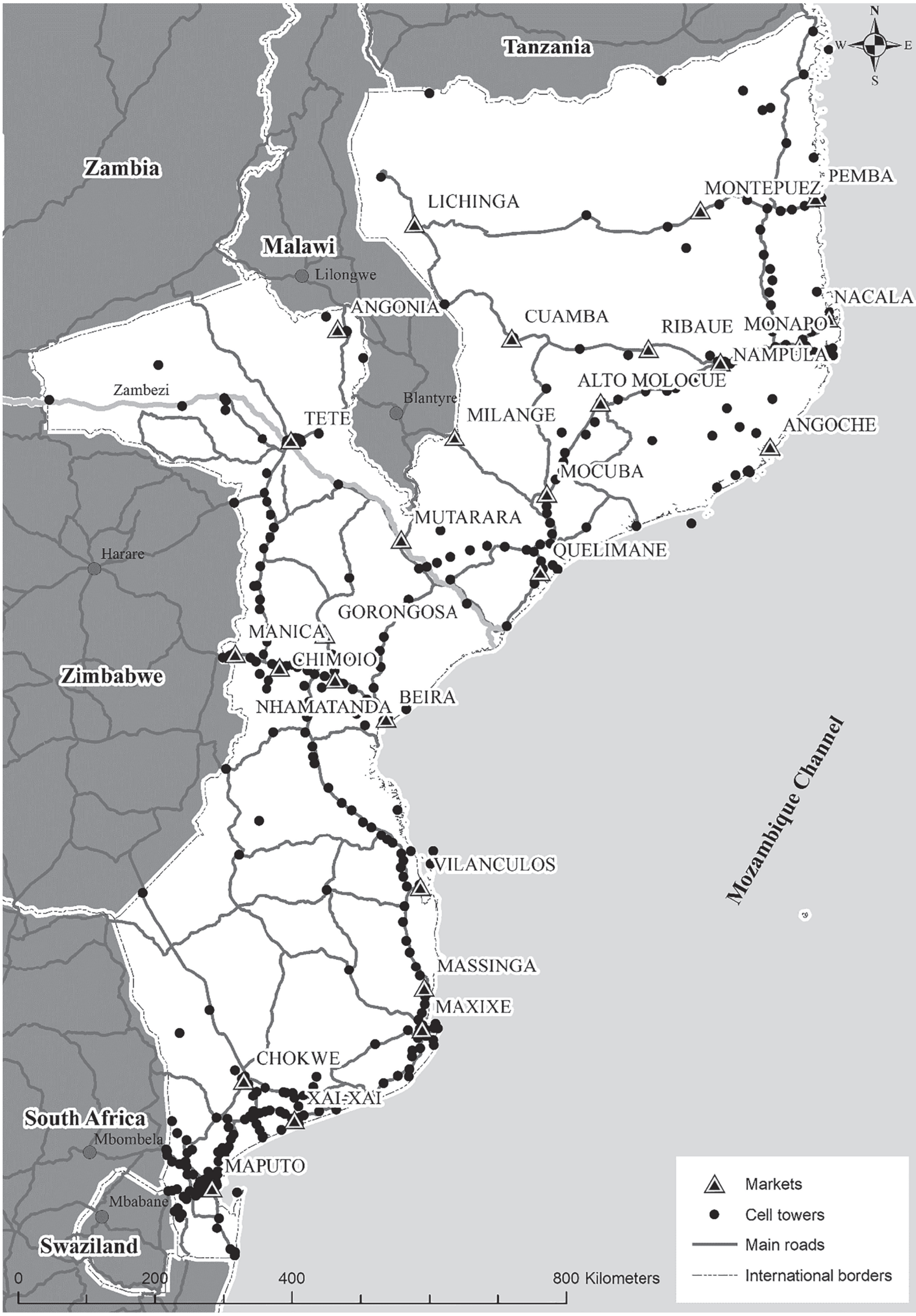

Figure 1. Mozambique: markets, roads and mobile phone towers.
Note: the figure shows the main roads, major cities and towns, and the network of mobile phone towers per ultimo 2009. Source: VU SPINlab.

drops in production.[5] Maize prices over time reflect how dependent Mozambique's agricultural sector is on the weather (Figure 2). Prices peaked in 2002 and 2006 due to droughts. Moreover, there is strong seasonality in maize prices: prices begin rising around September and peak around March. The degree of seasonality (Figures A1, A2, A3 and A4) is large with prices in the lean season twice as high compared to the post-harvesting months. These fluctuations are similar to observed seasonality in staple food prices in other sub-Saharan countries (Kaminski et al., 2016). Seasonality in maize prices is stronger – with higher highs and lower lows – and with a slightly diverging timing in rural areas compared to urban areas (Figure A5). Deficit urban areas, generally, have higher price levels and lower price volatility compared to surplus rural areas (Figure A6). This regularity is consistent with fixed per kg transaction costs (Fafchamps and Vargas-Hill, 2008).[6] Seasonality in maize prices also generates seasonality in spatial price differences between source and destination markets, which creates the arbitrage returns that drive long distance trade. Information on prices is systematically distributed: Sistema de Informação de Mercados Agrícolas (SIMA) collects and disseminates weekly data on agricultural prices throughout Mozambique since 1995.

2.3. Mobile phone roll-out

Similar to most other sub-Saharan countries , mobile phone technology was introduced in Mozambique at the end of the 1990 s and early 2000s (International Telecommunication Union (ITU), 2016). During the first three years (1997–1999) mobile phone towers were installed exclusively in the Maputo area. Mobile phone companies presumably concentrated on locations with a high population density and a relatively high per capita income, combined with low construction and maintenance costs for cell phone towers. In the years following the introduction, the network expanded rapidly, and around ten years later nearly all major cities and towns had access to the mobile phone network.[7] Visual inspection of the mobile phone network suggests that new mobile phone towers have been installed nearly exclusively along existing trunk roads (Figure 1). In later years the network was extended to more remote and less populated areas. However, rural areas in general, and the province of Niassa in the north in particular, remain underserved, both per km^2 land area and per capita.

3. Conceptual framework

I define transaction costs as the difference between the maize price at destination markets and the maize price at source markets. These costs capture the costs of all tasks, activities and claims related to taking maize from source markets to destination markets. The spatial price difference follows the identity

$$p_k - p_j = \tau_{jk} + c_{jk} + \mu_{jk} \tag{1}$$

where $p_j(p_k)$ is the market price in market $j(k)$, τ_{jk} is the (per unit) transport cost associated with moving maize grain from market j to market k, c_{jk} is the (per unit) cost of intermediaries not associated with transport, and μ_{jk} is the (per unit) mark-up of intermediaries. Under perfect competition the mark-up of intermediaries disappears ($\mu_{jk} = 0$) and equation (1) simplifies to

$$p_k - p_j = \tau_{jk} + c_{jk} \tag{2}$$

The mark-up of intermediaries (μ_{jk}) is determined by the extent of competition in trade and transport services. A few studies find evidence of substantial market power by intermediaries in developing country agricultural markets (Atkin and Donaldson, 2015; Bergquist and Dinerstein, 2020; Zant, 2022). The extent of competition is determined by the number or density of intermediaries, their geographical spread, entry of intermediaries, and the volume of trade flows. The extent to which intermediaries pass through cost reductions to consumers, given their marginal cost functions, along with the shape of the demand curve in destination markets, point at imperfect competition and a high mark-up of intermediaries (Bergquist and Dinerstein, 2020). Imperfect competition in the trading sector is also supported with Mozambique data (Zant, 2022). The introduction of mobile phones causes a drop in marginal costs, which enables intermediaries to operate in more markets and to increase the numbers of agents they search over (Allen, 2014). The reduction in costs potentially attracts new entry and possibly affects competition.

Similar to transaction costs, I define transport costs (τ_{jk}) to cover all costs associated with transporting maize from one market to another market. This catch-all term covers a wide range of activities: typical trade operations, but also wholesale activities, transport operations and retail activities.[8,9] Transport costs include costs of cargo collection, freight costs, fuel costs, time spent in transit, formal and informal costs of road tolls and police checkpoints, risk of damage and theft, insurance, and distribution costs in destination markets. Transport costs in sub-Saharan Africa are high relative to other countries (Teravaninthorn and Raballand, 2009; Atkin and Donaldson, 2015) and a large part of total transaction costs (Fafchamps et al., 2005). Transporters monitor information and take decisions on the basis of potential flows of merchandise and related transport opportunities and costs. Unlike pure trading activities that focus on spatial arbitrage returns, there is no publicly accessible source of information for long-distance trade that records and disseminates information on potential freight. Consequently transporters need to rely on information obtained through their own network or through traders. Access to mobile phone technology allows transporters to better identify transport opportunities, better identify potential flows of merchandise in geographically dispersed markets, make arrangements for return cargo more easily and avoid possible asymmetric information issues with traders.

On top of the efficiency in transport logistics, there are multiple other channels through which mobile phone coverage helps streamline and optimize the cost efficiency of transport services. Transporting merchandise entails a wide range of activities, requiring different pieces of information to take optimal decisions: traders need information on freight collection and backhaul cargo, on conditions and accessibility of roads, on weather, on prices and availability of fuel, on repair and maintenance of trucks, on insurance, on road tolls and police checkpoints and on other transport logistics. Much information is relevant for all transported commodities. There are, consequently, opportunities for

[5] In the 1999–2000 crop season, maize production declined 18 percent, primarily due to floods that devastated large areas of the centre and south (Abdula, 2005). More recently, from October 2006 to November 2007 and also in March and April 2019, tropical storms devastated agricultural crops in large parts of the country.

[6] Fafchamps and Vargas-Hill (2008) show that comparing the coefficients of variation of producer prices (or prices in source markets) and international prices (or prices in destination markets) is a simple reduced-form test of the form of transaction costs in the aggregate value chain. If $CV_{source} > CV_{destination}$ then transaction costs are fixed, if $CV_{source} = CV_{destination}$ then transaction costs move proportional to prices in destination markets, and if $CV_{source} < CV_{destination}$ transaction costs move more than proportional to prices in destination markets.

[7] The share of the population with mobile phone access increased from 0.3% in 2000 to 30.1% in 2010 (ITU, 2016). This share is well above the land line coverage of less than 0.4% in 2010.

[8] Typical trade operations include monitoring spatial arbitrage opportunities, undertaking spatial arbitrage transactions, contracting, collecting merchandise, distributing merchandise, funding & credit.

[9] Typical wholesale activities include collecting merchandise, storage, monitoring of temporal arbitrage opportunities; undertaking temporal arbitrage (purchase and sell; contracting); assembly, grading, quality control and packing of merchandise.

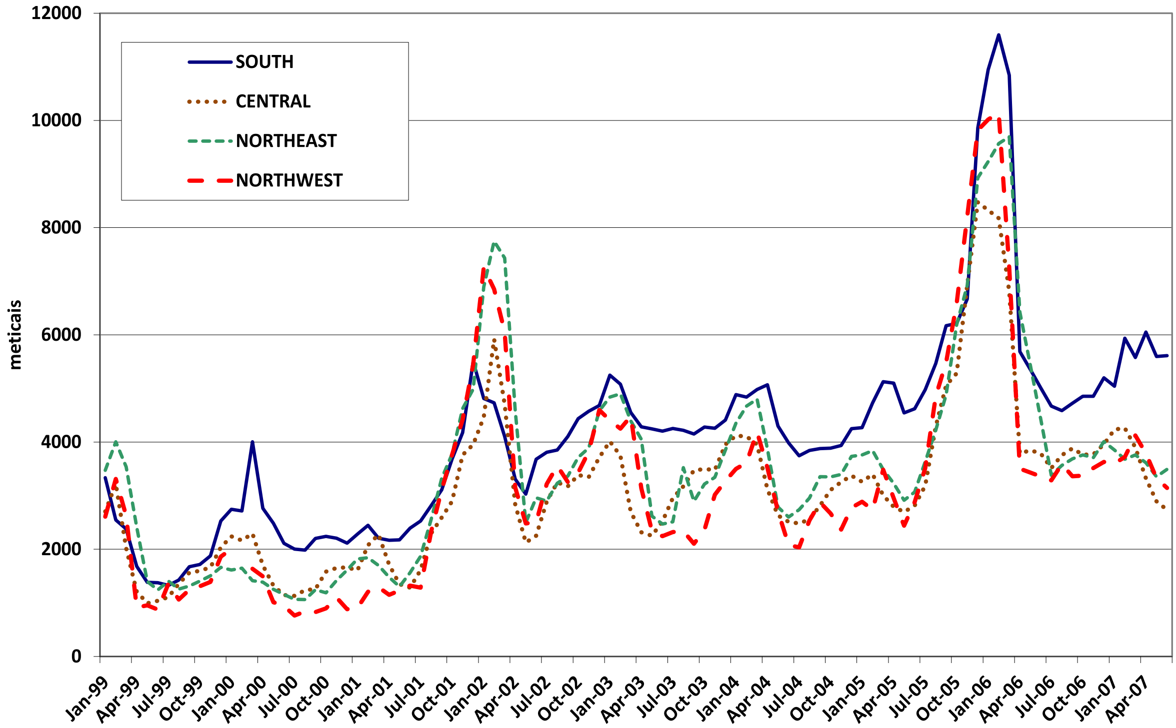

Figure 2. Maize price by region (nominal prices, January 1999-July 2007) Source: based on SIMA data.

economies of scope. Increased opportunities cause transported volumes of agricultural merchandise to grow and further exploit potential economies of scale. Mobile phone communication helps the transport sector to absorb this increase in volume efficiently. In summary, the growth in transported volume leads to economies of scale and scope in the transport operations which reduces per unit transport costs. Beyond transport costs and mark-ups of intermediaries there are a number of other components of transaction costs (non-transport related transaction costs, c_{jk}) associated with miscellaneous mechanisms like search and information (Aker, 2010; Allen, 2014), price uncertainty (Dillon and Dambro, 2017), contracting (Startz, 2021) and chain structure (Startz and Grant, 2022).

Taking expression (1) to the data is straightforward, but also reveals the limitations of the empirical work in the current study. With data on spatial price differences ($p_k - p_j$) and transport costs (τ_{jk}) I attribute impacts to total transaction costs and to transport related activities using the staggered mobile phone rollout. With robust results for both impacts it is also feasible to evaluate the relative size of reduced transport costs vis-à-vis total transactions, and, possibly, of non-transport related transaction costs. Finding evidence of mechanisms – how mobile phones affect competition, economies of scale and scope, and exit and entry – requires data on trade flows, number of traders, and scale and scope of transactions. Such an analysis is beyond the data used in this research.

4. Data and sample selection

4.1. Data, data sources and variable construction

The data on the roll-out of mobile phone infrastructure, sourced from the Ministry of Transport and Communication of Mozambique, contain 547 names of locations of mobile phone towers, their corresponding latitude and longitude coordinates, and the first year of operation.[10] The roll-out data that I have stretch from 1997 to 2009. It is unlikely that further extension of the mobile phone network stopped in 2009. However, with the limited number of markets in major towns and cities identified in the empirical estimations, the roll-out in my data set had already reached all markets by 2006 (Table A3). Mobile phone towers are first placed in city and town centers and, in later years in locations further away from these centers. These city and town centers in the roll-out data correspond with the markets identified in the price and transport cost data. This feature facilitates the linking of both data, since mobile phone coverage of markets is thereby insensitive to the range of a mobile phone tower.

Maize prices are from Sistema de Informação de Mercados Agrícolas de Moçambique (SIMA; https://www.agricultura.gov.mz/sima/), from their weekly publication Quente-Quente. SIMA, which started as a USAID-Michigan State University funded initiative, distributes weekly price bulletins, by email, through the Ministry of Commerce and through broadcasts on the national radio and television news in market programs. Dissemination of SIMA price bulletins started in 1995, well before the start of the mobile phone roll-out. Traders' interviews confirm the usefulness of the SIMA price information. I use the weekly retail market quotations of white maize grain in my analysis (Quadro 3, Preço e Mudança Percentual a Nível de Mercado Retalhista (MT/kg), grão de milho branco), recorded for 27 markets, from January 1999 to December 2007.[11,12] White maize grain is the dominant quality of maize produced, traded and consumed throughout the country. The 27

[10] Cell phone roll-out data were kindly made available by Jenny Aker.

[11] 'Weekly' means a price quotation on one day of the week (Monday; publication appears Wednesday) rather than an average of 7 observations of all days of the week.

[12] Alto Molocue, Angoche, Angonia, Beira, Chimoio, Chokwe, Cuamba, Gorongosa, Lichinga, Manica, Maputo, Massinga, Maxixe, Milange, Mocuba, Monapo, Montepuez, Mutarara, Nacala, Nampula, Nhamatanda, Pemba, Quelimane, Ribaue, Tete, Vilanculos en Xai-Xai. Figure 1 shows the locations of these markets in Mozambique.

markets are representative for both rural producer and urban consumer areas, and the period covers the time span of the roll-out of mobile phone infrastructure. The price data are collected by interviewing three randomly selected traders in each market on every Monday, for each commodity.

The data contain more than 6000 observations of maize prices, more than 50 % of the potential number of weekly observations. Unfortunately, there are missing observations in the price data (Table A1 gives an overview of the availability of data by year). However, missing observations are common in agricultural price data: they are correlated with the season and with occasional droughts, and due to a lack of transactions.[13] There could be a concern that the missing observations are correlated with mobile phone status. Intuitively, this is unlikely: missing observations due to seasonality will not be correlated with the mobile phone roll-out. Formal tests confirm that missing observations in prices, price differences and transport costs are not correlated with the mobile phone roll-out (Table A2).

Data on transports costs come from the same source as maize prices (SIMA). These data 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 and wholesalers in major source and destination markets. Transport cost data are specified by itinerary, by product and by the weight of the bags transported.[14] Transport costs are recorded for the period August 2001 to December 2010, with nearly-three quarters of the available observations before 2005 (Table A1). These data are not published anymore after 2010. Again, similar to the case of prices, missing observations in transport costs data are not correlated with the mobile phone roll-out (Table A2). Closer inspection of the transport cost data reveal that markets are either nearly exclusively source markets, or nearly exclusively destination markets (Tables A4 and A5). Only a few markets operate as assembly or transit markets, i.e. source vis-à-vis some markets and destination vis-à-vis some other markets.[15] In sharp contrast with other empirical evidence (Barrett, 1996, 2008; Alene et al., 2008; Moser et al. 2009; Allen, 2014) there is virtually no evidence of trade reversals in the transport cost data.[16] I exploit these properties when I construct samples for estimation (see below).

I use a number of miscellaneous variables from different sources. I take distance in kilometres, both road distance and Euclidian distance ("as the crow flies"), and traveling time in hours, from GoogleMaps, accessed in 2016. Road distance is useful for investigating heterogeneity in impacts, while Euclidian distance is useful for measuring the coverage of mobile phone towers. Decadal rainfall data by district are from FEWSNET.[17] I use these data, aggregated by season, to capture weather shocks on the supply side, including fluctuations due to flooding or drought. Data on population by cities and towns (markets) and by district are from three censuses (August 1997, September 2007, July 2016), published by Instituto Nacional de Estatistica Moçambique. I construct monthly population series for the relevant period by interpolation. I use population by market and population density by district as an approximation of (relative) demand or the ease of finding farmers with surplus maize. Along with the road distance between cities, I also use population data to construct network densities, an index variable that weighs the population of all surrounding markets inversely with road distance. Fuel prices (annuals, national), exchange rates and consumer price indices are from International Financial Statistics of the IMF, and used as covariates in the estimations, to convert series into national currency and to deflate nominal variables.[18] I use combinations of these variables to model the probability of access to mobile phones, the propensity score. With the exception of mobile phone roll-out and rainfall data, all data are obtained from public domain sources.

4.2. *Sample selection for estimation*

I measure spatial price differences as the difference in maize price between market j and k in period t, $p_{kt} - p_{jt}$ if $p_{kt} > p_{jt}$, where the higher price pertains to destination markets (k) and the lower price to source markets (j). This procedure yields a sample of more than 40,000 observations of spatial price differences that unambiguously tracks (reversals in) gross arbitrage returns (Table A1). Unfortunately only a subset of these spatial price differences reflect transaction costs.[19] How to find the subset of observations that is informative about trade costs?

I use source and destination information contained in the available transport cost data to select the relevant price difference data and rationalize this approach with reference to the Parity Bound Model (PBM, Baulch 1997, Moser et al. 2009). The PBM, which is rooted in competitive spatial price equilibrium theory (Fackler and Goodwin, 2001), distinguishes three regimes: 1. spatial price difference are less than transaction costs (no or loss making trade); 2. spatial price differences are equal to or slightly above transaction costs (efficient and profitable trade), and 3. spatial price differences are larger than transaction costs (profitable but unexploited trade opportunities). Regimes 1 and 2 are associated with competitive spatial price equilibrium and market integration; regime 3 is associated with non-integrated markets, and not consistent with competitive spatial price equilibrium. Regime 3 observations are not informative about actual transactions costs.

Unfortunately, it is not straightforward to identify each regime, especially if data on trade flows are lacking. Baulch (1997) proposes an extrapolation of transaction costs (labelled as transfer costs, and observed for one period) to identify different regimes. I follow a data-driven strategy: I exploit the properties of the transport cost data (source and destination of trade routes, and number of times specific source market and destination markets are recorded; see Tables A4 and A5). I make the assumption that transport costs are only recorded if trade is likely and, consequently, dates and market pairs in the transport cost data can therefore be considered a reflection of actual trade (or regime 2 observations). As a first step I match the sample of spatial price differences to the sample of transport cost data, by market pair and year (1). Next, I postulate that markets are either exclusively source markets, or exclusively destination markets, based on the trade pattern reflected in the transport cost data (see discussion at the start of this section and Tables A4 and A5).[20] The identification of source and destination markets is also in line with complementary information on per capita production of maize, availability of data on growers' prices, population size by market and location (not reported, available from the author), and

[13] This explanation of missing price data is confirmed by author's communications with SIMA staff. The claim that the price survey was run every market week, but that maize was occasionally unavailable in the market is further supported and strengthened by the fact that the weekly SIMA bulletins are available for all weeks, and prices of other crops are, generally, available during the market weeks in which maize prices are missing.

[14] Differences in volumes for different crops justify separately recorded per kg transport costs.

[15] Examples are Tete, Nampula and Chimoio: maize in Tete is sourced from Angonia and Chimoio, and further transported to Maxixe, Maputo, and Massinga. Likewise, maize in the Nampula market is sourced from Alto Molocue and Mocuba, and further transported to Maxixe, Maputo, Xai-Xai and Beira. See also Table A5.

[16] Transport costs recorded both ways in the same year only occur with four market pairs (single observations) and only in the case of one market-pair (Tete-Chimoio) with more than 1 observation.

[17] Rainfall data from FEWSNET were made kindly made available by Benedito Cunguara.

[18] Base year for deflation is 2010 and 1 US$ = 33,960 meticals (2010).

[19] *Atkin and Donaldson (2015)* note in this connection: 'Spatial price gaps are only rarely directly informative of trade costs'.

[20] Source markets: Alto Molocue, Angonia, Gorongosa, Lichinga, Manica, Mocuba, Montepuez, Nhamatanda and Ribaue; Destination markets: Beira, Massinga, Maputo, Maxixe, Nacala, Pemba, Quelimane, and Xai-Xai.

maize price volatility (Figure A6), and corresponds with stylized facts extracted from the Mozambique maize marketing reports (e.g. Abdula, 2005; Tschirley et al., 2006). The identification of exclusive source and destination markets justifies extending the sample with observations from typical source markets (2), from typical destination markets (3), and both from typical source and destination markets (4). These sample specifications are used in the estimation of spatial price differences (Table 1) and transport costs (Table 2).[21]

For the price level estimations (Tables 3 to Table 5), and to verify that my estimates are robust, I constructed additional samples that restrict prices to pairs with at least three transport cost observations per year (2), and to post harvest months (4). Both sample adjustments are intended to better capture observations at source and destination markets that correspond with (potential) long distance trade flows. Trade flows are more likely if transport costs are more often recorded. Likewise, trade flows are also more likely in post-harvest months.[22]

5. Empirical strategy

5.1. Basic specification

In order to compare market pairs with and without mobile phone coverage, I propose the following two way fixed effects specification (TWFE) with market pair and time fixed effects:

$$(p_k - p_j)_t = \beta_0 + \beta_1 cell_{jkt} + \boldsymbol{X}_{jkt}\gamma + \eta_{jk} + \theta_t + \varepsilon_{jkt} \tag{3a}$$

$$\tau_{jkt} = \beta_0 + \beta_1 cell_{jkt} + \boldsymbol{X}_{jkt}\gamma + \eta_{jk} + \theta_t + \varepsilon_{jkt} \tag{3b}$$

where $(p_k - p_j)$ is the spatial price difference and τ_{jk} are transport costs between markets k and j, $cell_{jkt}$ is a binary variable equal to 1 in period t if both markets k and j have mobile phone towers, and zero otherwise. The vector $\boldsymbol{X}_{jkt}$ represents variables that influence price dispersion and transport costs, such as drought and flooding in sources markets, fuel prices reflecting trade costs, and differences in demand across markets due to population size and income. Parameters η_{jk} and θ_t are market pair and time fixed effects, and ε_{jkt} is an error term with zero mean. To capture geographically diverging developments over time, I include source and destination specific linear trends. Likewise, I control for geographically diverging seasonality in maize prices (see previous section and Figures A3 to A5).[23] The core data (market prices and transport costs) are recorded by week, and time (subscripts t) in the specification refers to weeks. Many variables, however, including seasonality and trends have a monthly frequency, with the exception of the impact variable and last-season rainfall which are annual. The parameter of interest is β_1, which measures the impact of mobile phones on either spatial price dispersion or on transport costs. I am particularly interested in the impact of mobile phones on transaction costs vis-à-vis their impact on transport costs. The key identifying assumptions are that trends in outcomes before the introduction of mobile phones are the same for both intervention and non-intervention market pairs, and that the rollout of the mobile phone network is exogenous to (spatial price differences of) maize prices and transport costs.

Shocks to demand, supply and trade may affect measured impact in my observational data and, consequently, I control for these factors by including time varying covariates ($\boldsymbol{X}_{jkt}$). I have used a variety of variables: the size of population by city (market) to account for differences in demand across markets, population density by district and network density (an index variable that weighs population of all surrounding markets inversely with road distance) to account for differences in economic activity across markets, rainfall during the last season as key determinant of supply shocks in view of the predominantly rain-fed nature of agriculture, and fuel prices since fuel costs are a major part of transport costs.

5.2. Testing equality of pre-intervention trends of treated and non-treated

The TWFE approach requires that pre-intervention outcomes for intervention and control groups follow parallel trends. Following the empirical literature (Autor, 2003), I graphically investigate if the parallel trend assumption is satisfied. The graphical presentation also makes it possible to assess the dynamic path of impact. The results of the parallel trend test, shown in Figure A9, confirm that both spatial price differences and per kg transport costs are on parallel trends before the introduction of mobile phones: all "before" coefficients are not statistically different from zero. The figures also support a statistically significant negative impact after the introduction of mobile phones, and these impacts appear to be stable over time. Finally the figures suggest that the impact on price dispersion is very close in size to the impact on transport costs (and occasionally even smaller!).

5.3. Addressing potential selection bias

The roll-out of mobile phone technology clearly suggests several drivers guiding investments in the expansion of the mobile phone network (population density, road network, remoteness). To address potential selection bias, I employ propensity score matching (PSM). I first model the probability of access to mobile phones, the propensity score, using observable determinants of the roll-out of the mobile phone network. Then, I match and compare observations with a similar propensity score, both with and without access to mobile phones. To support the PSM estimation outcomes, I assess the quality of the PSM estimation: I discuss if the determinants of the propensity score meet requirements, how well the propensity score is explained, if the matching algorithm is robust, if the common support condition is met, and the resulting quality of the matching outcome. These results are documented in the next section and in the appendix.

The empirical set-up of the mobile phone roll-out has multiple periods, multiple markets pairs and interventions at different points in time. A small recent literature has pointed to potential inconsistencies and biases in estimated impacts in staggered intervention designs and has proposed diagnostic techniques and estimation techniques that control for these inconsistencies (Goodman-Bacon, 2018; de Chaisemartin and d'Haultfœulle, 2020; Jakiela, 2021; Callaway and Sant'Anna, 2021). Unfortunately the data for the current research are not suitable for using these estimation techniques (Callaway and Sant'Anna,

[21] Admittedly, a more subtle sample construction would have been feasible with trade flow data (as positive trade flows between markets require the spatial price difference to be equal or higher than the per unit transaction costs Allen, 2014). Unfortunately trade flow data are lacking.

[22] Most farm households sell maize directly after harvest, during a restricted time span, often not longer than three to five months. Evidence from household surveys indicates that more than 80% of all maize grain transactions take place during five consecutive months, from June to October (based on Trabalho de Inquérito Agrícola (TIA) for 2005 and 2011 (Figure A8). The seasonality in prices mirrors the supply of maize in the market and the likelihood of trade between source and destination markets, and suggests an earlier start of the period in which trade takes place (Figures A3 and A4). The concentration of farmers' sales in a few post-harvest months is widespread in sub-Sahara Africa (Barrett, 2008). Conversely, during the lean season, from November to March when markets are 'thin', prices tend to fluctuate in an erratic way. Since erratically fluctuating prices (and related spatial price differences) are unlikely to be informative about regular trade patterns, there is a case to exclude these observations.

[23] A full specification of estimated equations for spatial price differences and transport costs including seasonality and trends by source and destination is in the Appendix.

2021).[24]

Since spatial price dispersion is partly determined by transport costs (see equation (1)), I can further exploit the information contained in spatial price differences and transport costs by combining these data. I regress price dispersion adjusted for per kg transport costs on the cell phone intervention variable, and include covariates and fixed effects

$$\left(p_{kt} - p_{jt}\right) - \tau_{jkt} = \beta_0 + \beta_1 cell_{jkt} + \boldsymbol{X}_{jkt}\gamma + \eta_{jk} + \theta_t + \varepsilon_{jkt} \tag{4}$$

A positive significant coefficient β_1 offers an estimate of the impact on non-transport cost related transaction costs (c_{jk}) and the mark-up (μ_{jk}), and should be similar in size to the difference of the cell phone coefficients from specification (3a) and 3(b).

Once there is evidence that spatial price differences have declined, it is informative to investigate how mobile phones impact price levels in source markets and in destination markets. In other words, is the reduction in spatial price differences associated with a (relative) increase in source market prices, or a (relative) decrease in destination markets prices, or both. I estimate the equation

$$p_{jt} = \beta_0 + \beta_1 cell_{jt} + \boldsymbol{X}_{jt}\gamma + \eta_j + \theta_t + \varepsilon_{jt} \tag{5}$$

where subscripts *j* refers to either a set of source markets or a set of destination markets. If source and destination markets are combined in one estimation, the differential impact can be estimated by interacting the intervention variable with either source or destination,

$$p_{jt} = \beta_0 + \beta_1 cell_{jt} xsource + \beta_2 cell_{jt} xdestination + \boldsymbol{X}_{jt}\gamma + \eta_j + \theta_t + \varepsilon_{jt} \tag{6}$$

Equation (6) allows me to exploit the estimated impact on price differences as a restriction on the coefficients, $\beta_2 - \beta_1 =$ *estimated reduction in transaction costs*.

6. Estimation and robustness checks

6.1. Impacts of mobile phones on spatial price differences

I first report TWFE estimates of equation (3a). Column (1) in Table 1 reports the estimation based on a sample that matches the spatial price difference data by market pair and year of the transport cost data. Columns (2) to (4) extend the sample by including market pairs with typical destination markets (2), typical source markets (3), and the combination of these markets (4). Following standard practice I report robust standard errors clustered by market pair (Bertrand et al., 2004).

Since my data are observational, both price dispersion and transport costs may be influenced by time varying observables. As indicated, I control for a variety of supply, trade and demand effects by including covariates (market population, district population density, and network density, by source and destination market, last season's rainfall and fuel prices by source market). The number of included covariates is limited and arbitrary: several alternative, and potentially relevant, controls are considered. Road infrastructure is an obvious candidate. However, data on developments in road infrastructure by itinerary (upgrades, maintenance, but also degradation) are lacking. Hence, I cannot rule out that that part of the measured reduction in spatial prices could be due to changes in road infrastructure during the mobile phone roll-out. Improvement (deterioration) on this account leads to an upward (downward) bias of estimated impacts. However, improvements (or deterioration) of the entire road network – characterized as a time trend – are automatically captured by time fixed effects.

The results in the upper panel of Table 1 show a statistically significant reduction in price dispersion between markets as a result of the introduction of mobile phones, across all samples. Estimates including covariates, reported in the lower panel of Table 1, further confirm the upper panel results. The impacts are consistently statistically significant. Expressed as a percentage of average pre-mobile-phone price levels, the reduction in spatial price differences has a size of 9 %-15 %. Evaluated at the average pre-mobile-phone spatial price *differences* – reflecting the change that traders experience – the reduction is much larger (35 %-41 %). The reduction is smaller if I include more observations in the estimation sample (columns (2) to (4)). My estimates also suggest that impacts increase with road distance.[25]

Table 1
Impact of mobile phones on dispersion of maize prices.

dependent variable: maize price difference between markets (p_{kt}–p_{jt}, $p_{kt} > p_{jt}$)				
	(1)	(2)	(3)	(4)
cell phone	−938.4***	−713.8***	−466.4***	−814.9***
	(350.7)	(120.9)	(128.7)	(186.4)
covariates	no	no	no	no
adj R^2	0.661	0.535	0.517	0.570
cell phone	−1228.6***	−746.9***	−589.7***	−802.7***
	(367.1)	(112.6)	(99.5)	(172.4)
covariates	yes	yes	yes	yes
adj R^2	0.679	0.543	0.533	0.589
no. of observations	3462	15,019	16,276	8317

Note: Weekly maize price data are from January 1999 to December 2007 (source: SIMA) and deflated with the national consumer price index (2010 = 100). All estimations include time and market pair fixed effects, and seasonality and trends by source and destination. Equations are estimated using OLS. Column (1): the sample is matched by market pair and year to the available transport cost observations; in column (2): as (1), plus market pairs with typical production areas as source markets; in column (3): as (1), plus market pairs with typical terminal markets as destination market; column (4) combines (2) and (3). Covariates are: market population, district population density and network density, by source and destination market, last season's rainfall and fuel prices by source market. Robust standard errors in brackets below the coefficient are clustered by market pairs. *p < 0.10, **p < 0.05, ***p < 0.01.

6.2. Impacts of mobile phones on transport costs

I proceed by estimating the impact of mobile phone introduction on transports costs: estimation results are reported in Table 2. The applied specification follows the specification used in the spatial price difference estimations: in all estimations I have included time and market pair fixed effects, and seasonality and trend by source and destination. As a corollary to the spatial price difference estimations I investigate whether my outcomes are robust to restricting samples to typical source markets, typical destination markets and the combination of these restrictions (Table 2, columns (2) to (4)). In contrast to the price differences samples, these restrictions lead to smaller rather than larger samples.

Inspecting the upper panel of Table 2, the impact of mobile phones on transport costs is statistically significant at the 1 % level across all samples. Estimations including covariates hardly differ: coefficients in the lower panel of Table 2 are statistically equivalent to their "no covariates" counterparts. The introduction of mobile phones has reduced transport costs by 19 %-27 %, evaluated at the average pre-mobile phone per kg transport cost. The impact is large, especially relative to the impact on transaction costs (see Table 1): on average, between 70 % and 80 % of the reduction in transaction costs is due to lower transport costs.

[24] Key problems in implementing the Callaway and Sant'Anna (2021) estimation technique are the different frequencies of the data (monthly prices & transport costs, annual interventions), the imbalanced panel and the large number of equations to compare.

[25] I explore the relationship with road distance by interacting the mobile phone intervention variable with road distance. The coefficients of higher road distances are (weakly) significantly larger relative to lower road distances (results not reported, available from the author).

Table 2
Impact of mobile phones on transport costs.

dependent variable: transport costs of maize grain per kg (tc_{jkt})				
	(1)	(2)	(3)	(4)
cell phone	−502.0***	−488.7***	−498.3***	−576.8***
	(154.1)	(168.6)	(178.1)	(213.8)
Covariates	no	no	no	no
adj R^2	0.818	0.851	0.838	0.843
cell phone	−446.6***	−587.8***	−573.0***	−466.7**
	(144.3)	(201.6)	(197.7)	(183.2)
Covariates	yes	yes	yes	yes
adj R^2	0.816	0.848	0.838	0.842
no. of observations	1126	771	792	841

Note: Weekly transport cost data are from August 2001 to December 2010 (source: SIMA) and deflated with the national consumer price index (2010 = 100). All estimations include time and market pair fixed effects, and seasonality and trends by source and destination. Equations are estimated using OLS. Column (1): full sample; column (2): market pairs with typical production areas as source markets, column (3): market pairs with typical terminal markets as destination market and column (4) combines (2) and (3). Covariates are: market population, district population density and network density, by source and destination market, last season's rainfall and fuel prices by source market. Robust standard errors in brackets below the coefficient are clustered by market pairs. *p < 0.10, **p < 0.05, ***p < 0.01.

6.3. Robustness checks: Propensity score matching

In order to address possible selection bias arising from the non-experimental setting, I verify my results by estimating the impact of mobile phones using propensity score matching (PSM). I include details on these estimations in the Appendix (Table A7 to A10 and Figure A10). The PSM impact estimations, reported in Tables A7.1 and A7.2 , confirm the estimation results obtained through TWFE-OLS, reported in Tables 1 and 2. Impact coefficients (ATT) are in the range of the corresponding TWFE-OLS estimates. The transport cost estimations (Table A7.2) perform less, most likely due to a lack of statistical power. Testing the robustness of the matching algorithm by repeating the PSM estimation with Nearest Neighbour (NN) as a matching algorithm generates similar results as with Kernel Matching, though with lower accuracy (Tables A10 and A10.2). Nevertheless, the relative similarity of estimated impacts with different types of matching algorithms and TWFE-OLS offers confidence about the robustness of the kernel matching procedure and about the TWFE-OLS impact estimates.

6.4. Net transaction costs

I now estimate spatial price differences adjusted for per kg transport costs (see *Empirical strategy*, equation (4)). This estimation requires combining spatial price differences with transport cost data. A closer inspection of the transport cost data reveal that these data only match by market-pair plus date for a very small number of observations (less than a quarter of the transport cost observations). Additionally, a substantial share of per ton per km transport costs are well above the corresponding (per ton per km) spatial price difference. I also find that the standard deviation and skewness of per ton per km transport costs are large (Table A6). The small number of exact matches, and the relative size and volatility of the transport cost data are problematic for estimating the net transaction cost equation.[26] I have experimented with several transformations of the transport costs data in order to increase the number of matches with spatial difference data. The transformations aim at removing potential errors, or modeling possible over-reporting by traders in the transport cost data. For example, I have taken means, medians or minimum values per quarter or per year using the assumption that per kg transport costs for a specific market pair do not vary within a year or within a quarter. Median values (instead of means) control for skewness and minimum values control for over-reporting. Negative values of net transaction costs are also problematic: I experimented by both restricting estimations to positive values of net transaction costs, by truncating negative values to zero, or by including negative net transaction costs.

Unfortunately the estimation results of the mobile phone impact on net transaction costs are not good (Table A11). Estimated impacts fluctuate heavily, are never significantly different from zero, and are inaccurately estimated. I attribute the statistically disappointing results to measurement error in the (price and) transport cost data. The only positive claim that I can make is that the insignificance of the estimated impacts is consistent with previous results.

6.5. Potential threats and alternative explanations

I discuss a number of concerns that may jeopardize my interpretation of the estimated impacts. The first concern relates to 'other factors': other factors may have triggered both the placement of mobile phone towers and supply and/or demand fluctuations in the maize markets. Since installing mobile phone infrastructure does not take place overnight, these investments are unlikely to be triggered by year to year fluctuation of any 'other factor'. However, trends and structural developments of 'other factors', for example climate change, population growth or income, potentially play a role in investing in mobile phone infrastructure. Such factors may also affect the structural development of the maize market. These trends and structural developments take years to develop, are difficult to forecast and have huge and varying lags. It is therefore safe to assume that such developments are independent of decisions about investment in mobile phone infrastructure.

A second concern is about traders migrating in response to availability of mobile phone services. Traders may transfer their activities to markets and itineraries that have access to mobile phone services. Increased trader activity will increase trade flows and reduce price differences between markets, and the opposite occurs in markets and itineraries that have no access to mobile phone services. Such migration will therefore bias estimated impacts upwards. Formally I cannot rule out this possibility: I do not have data on the number of traders active in different markets and on different itineraries. I also do not know the size of trade flows between markets or their development over time.[27] Nevertheless, large scale trader migration is unlikely given market uncertainties and potential costs. A third concern, related to the previous one, is increased entry (or exit) of traders in response to the availability of mobile phone services. It seems logical that entry and exit should explain at least some of the increased efficiency of markets, especially in the long run. Again, I cannot rule out this possibility and I have to assume that the associated bias in estimates is negligible. This assumption can only be justified by arguing that changes in trade intensity (increases in trading capacity, number of traders, migration) take time to be realised and, given the short estimation period in this study, are therefore not likely to be large.

A fourth concern is that the availability of mobile phone services (and increased trade) may trigger a supply response from maize growers, since maize growers benefit from improved transparency of market prices of inputs and outputs and lower trade costs, leading to higher productivity, higher farm gate prices and higher profitability. Consequently, maize growers may have an incentive to increase production which affects the maize market prices and spatial price differences. Elsewhere I have investigated the impact of mobile phones on

[26] For the estimation of impact on transport costs these issues are less important since they are absorbed by trade-pair and week fixed effects.

[27] A possible increase in domestic trade flows could spill-over to international trade. However, I could not detect a significant impact of mobile phones on aggregate bilateral trade flows with neighboring countries (results available from the author).

farm gate prices (Zant, 2019): I find no support for higher farm gate prices. Given this evidence it is unlikely that a supply response from maize growers related to the introduction of mobile phones affects market outcomes and spatial price differences.

A final concern is about collusion: mobile phone services may enhance collusion between traders by facilitating communication and coordination. This may help traders keep prices low in source markets and high in destination markets. Collusion between traders due to the introduction of mobile phones increases the spatial price difference and thereby dampens impact. With many small-scale and informal traders, dispersed over a vast country and a multitude of itineraries, involving millions of trade transactions, it is difficult to believe that the measured impact is meaningfully affected by collusion. The evidence on changes in price levels and the analysis of who benefits from improved efficiency suggests that traders have less power to affect prices in destination markets. Whether the power to affect prices in source markets is due to collusion or something else (for example, asymmetric information between farmer and trader, a comparative advantage of traders in traders' services, or a smaller number of agents on either side of the market) is difficult to answer (see also Zant, 2019). Again, to establish mechanisms, important for policy, requires detailed data on producers, traders, trade-flows and consumers.

6.6. Who benefits from access to mobile phones?

A welfare analysis – assessing which group benefits the most from access to mobile phones – is unfortunately not possible with the current data. However, there are some analyses I can perform to shed light on this issue. In the previous sections I found a statistically significant decrease of spatial price differences. With perfect competition among traders, this reduced price difference comes from lower prices in destination markets, higher prices in source markets, or a combination of these.[28] If the entire decrease in price dispersion is due to a decrease of prices in destination markets, mobile phones mostly benefit consumers. Alternatively, if the entire decrease in price dispersion is due to an increase of prices in source markets, mobile phones mostly benefits producers.[29]

I empirically investigate diverging impacts on source markets and destination markets by estimating essentially the same specification as in the case of spatial price differences, but now price levels in destination markets, or price levels in source markets, is the dependent variable rather than price differences across markets. Consequently, I only include one set of seasonality and trend variables (see equation (5)). Market fixed effects in these estimations are not associated with transport costs or the road distance between markets. I use the following sample selection procedure to improve accuracy and check robustness. Similar to the spatial price difference estimations, I match the sample of price level observations to the sample of transport cost observations, by year and market (column (1)). Next, in order to increase reliability in column (2) I require a minimum of three transport cost observations by year and market. Finally, I add to the original column (1) sample typical source (destination) markets in column (3), and I restrict column (3) sample to typical trading months in column (4) (see Tables 3 to 5).

I first estimate the equations separately for source markets (Table 3) and destination markets (Table 4). The estimation results for source markets (Table 3) show a statistically significant positive coefficient at

Table 3
Impact of mobile phones on maize prices in source markets.

dependent variable: maize prices in source markets (p_{kt})	(1)	(2)	(3)	(4)
cell phone	1245.9***	1351.2*	550.3**	873.0***
	(309.2)	(772.8)	(262.6)	(328.2)
adj R^2	0.839	0.839	0.823	0.768
no. of observations	2399	1814	3171	2185
mean dependent variable:				
before intervention (n)	7355.5	7453.8	5743.3	4945.3
	(268)	(250)	(738)	(541)
after intervention (n)	6664.2	6336.2	6536.6	5870.4
	(2131)	(1564)	(2433)	(1009)

Note: Weekly maize price data are from January 1999 to December 2007 (source: SIMA) and are deflated with the national consumer price index (2010 = 100). All estimations include time and market fixed effects, and seasonality and trends, by markets. Equations are estimated using OLS. Column (1): the sample is matched by source market and year to the available transport cost observations; column (2) as column (1) but requiring at least 3 transport cost observations per market and year; column (3) as column (1) including typical source markets; column (4) as column (3) with only observations from April to October. Robust standard errors in brackets below the coefficient are clustered by market. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 4
Impact of mobile phones on maize prices in destination markets.

dependent variable: maize prices in destination markets (p_{jt})	(1)	(2)	(3)	(4)
cell phone	−1312.0**	−1077.7**	−790.7**	−828.4***
	(544.0)	(451.1)	(340.8)	(270.4)
adj R^2	0.804	0.812	0.782	0.782
no. of observations	2718	2201	3287	2027
mean dependent variable:				
before intervention (n)	7236.6	7597.7	5930.2	5387.4
	(127)	(63)	(472)	(323)
after intervention (n)	7216.0	7384.2	7185.4	6587.3
	(2591)	(2138)	(2815)	(1704)

Note: Weekly maize price data are from January 1999 to December 2007 (source: SIMA) and are deflated with the national consumer price index (2010 = 100). All estimations include time and market fixed effects, and seasonality and trends, by markets. Equations are estimated using OLS. Column (1): the sample is matched by destination market and year to the available transport cost observations; column (2) as column (1) but requiring at least 3 transport cost observations per market and year; column (3), as (1) including typical destination markets; column (4) as (3) with only observations from April to October. Robust standard errors in brackets below the coefficient are clustered by market. *p < 0.10, **p < 0.05, ***p < 0.01.

the 5 % level (3 out of 4) and at the 1 % level. Impact of mobile phones on prices in source markets ranges from + 550 to + 1351, an increase in prices of 9.6 % to 18.1 %, expressed as a percentage of average pre-intervention prices. However, the source market estimations are not stable: impacts vary substantially, are sensitive to outliers, do not improve in accuracy if restricted to source markets and are, in one case, only weakly significant. The coefficients for source markets also fluctuate more than the coefficients for destination markets. I attribute these weak results to the large geographical spread of source markets, some of which are close to borders (Malawi, South-Africa), to the mixed role of these markets (purely producer area market, assembly market, or assembly market with a large local demand) and to the role of the Zambezi river in trade. There is some support for geographical heterogeneity: markets north and south of the Zambezi appear to respond differently (Tables A12 and A13).

The estimations for destination markets (Table 4) indicate a statistically significant consistent reduction in prices in destination markets,

[28] Reduced transaction costs are also consistent with a price level decrease in destination markets that exceeds the price level decrease in source markets, or a price level increase in destination markets that falls short of the price level increase in source markets.

[29] Strictly I need to distinguish producers and producer areas. To determine if producers benefit from mobile phones I need to investigate farm-gate or producer prices vis-à-vis market prices in producer areas (Zant, 2019). Additionally this exercise ignores the possibility that traders capture (part of) the benefits.

Table 5
Impact of mobile phones on maize prices: constrained estimation.

dependent variable: maize prices in both source and destination markets (p_t)				
	(1)	(2)	(3)	(4)
cell phone	−817.1***	−1017.8*	−994.9***	−842.2***
in destination markets	(117.5)	(599.4)	(235.0)	(231.4)
cell phone	−17.1	−217.8	−194.9	−42.2
in source markets	(117.5)	(599.4)	(235.0)	(231.4)
RMSE	661.0	1130.4	1252.9	1173.3
no. of observations	3934	3455	5212	3630

Note: Weekly maize price data are from January 1999 to December 2007 (source: SIMA) and are deflated with the national consumer price index (2010 = 100). All estimations include time and market fixed effects, and seasonality and trends, by markets. Equations are estimated using OLS with a constraint on the cell phone coefficient (cell phone$_{\text{destination markets}}$ – cell phone$_{\text{source markets}}$ = –800). The samples in column (1) to (4) are combinations of the samples in the corresponding columns of the previous two tables. In all samples each date is matched with the sample of price difference estimations (Table 1, column 4). Robust standard errors in brackets below the coefficient are clustered by market. *p < 0.10, **p < 0.05, ***p < 0.01.

for all four samples, where the significance level varies between 1 % and 5 %. Impact ranges from –791 to –1312, a decrease in prices of 13.3 % to 18.1 % expressed as a percentage of average pre-intervention prices. The estimated coefficients are more accurate when I include typical destination markets and when I restrict my sample to typical trading months (column 3 and 4).

Are the estimated coefficients for sources markets and destination markets mutually consistent? And are the estimated coefficients for sources markets and destination markets consistent with the estimated impact of mobile phones on spatial price differences? Consistency of the price level impacts with the spatial price difference estimation requires that the change in destination market prices minus the change in source market prices equals the change in price differences ($\Delta p_{kt} - \Delta p_{jt} = \Delta\left(p_{kt} - p_{jt}\right)$). On the basis of price difference estimations (Table 1, column 4), we expect the difference between the change in destination markets and the change in source markets is around −800. I combine the lowest and highest impact on price levels in source and destination markets, from Tables 3 and 4, $\Delta p_k - \Delta p_J = -1312 - (+1351) = -2663$ (=highest reduction in destination markets combined with highest increase in source markets) or $\Delta p_k - \Delta p_J = -791 - (+550) = -1341$ (=lowest reduction in destination markets combined with lowest increase in source markets). These calculations show that the change in the price difference based on estimated price level impacts (Tables 3 and 4) is outside the range of estimated impacts based on price differences (Table 1).

Since price level estimations, estimated separately for source and destination markets, do not generate results that are consistent with price difference estimations, my next step is to incorporate the consistency requirement in a price level estimation, jointly for source and destination markets (equation (6)). Hence, I re-run estimations with source and destination prices combined, and two impact variables – one for source markets and one for destination markets – along with a constraint on the coefficients ($\Delta p_{kt} - \Delta p_{jt} = -800$).[30] To guarantee that, for each date, each source (destination) market has at least one destination (source) market, I restrict the sample in the constrained price level estimations to the sample of the price difference equation (Table 1, column 4).

The results of these estimations, reported in Table 5, confirm a sizeable reduction of prices in destination markets and, if any, a much smaller and statistically insignificant increase of prices in source markets. I show that these results are robust by re-estimating the constrained price level equations under the condition that, for each date, observations of prices in source and destination market combine to at least 20 different market pairs (Table A14).[31] Evaluated at mean prices before the introduction of mobile phones this outcome corresponds with a price reduction of 11 %-17 % in destination markets and, at most, a price increase of 3 % in source markets. On the basis of this evidence I conclude that the benefits of the improved efficiency are biased towards destination markets. The larger reduction in market prices on the consumption side possibly reflects more competition and more alternatives for substitution in destination markets, or more bargaining power for traders in source markets (vis-à-vis farmers) relative to destination markets (vis-à-vis retailers or final consumers). But these claims are conjectural and cannot be verified.

In most SSA countries poverty is high in remote rural areas, and commonly higher than in urban areas. Mozambique is no exception. A distribution of benefits of reduced transaction costs that is biased towards destination markets in urban areas is therefore not helpful in poverty alleviation. Even if farmers are net buyers, their purchases are concentrated in the lean season, a season without long distance trade but with high rural prices. The lack of benefits for farmers found in the literature (Muto and Yamano, 2009; Fafchamps and Minten, 2012; Tadesse and Bahiigwa, 2015) is consistent with lower transaction costs being driven by reduced transport costs. It also suggests that policymakers should not view mobile phones as the silver bullet that increases farm gate prices, or, more generally, prices in producer areas. Similar distributional welfare impacts are found to be the result of policies that promote fertilizer and high yielding crops, or in general Green Revolution policies (Evenson and Gollin, 2003), or policies that aim to reduce fuel subsidies (Fuje, 2018). Despite the wider usefulness of improvements in communication and transportation infrastructure, different policies are needed to reach the rural poor. Promising candidates are policies that reduce asymmetric information between farmers and traders (Zant, 2019), and policies that increase the asset base of farmers (Boughton et al. 2007).

A major shortcoming of the analysis of distributional implications is that the role of intermediaries is not explicitly modeled: benefits accrue to either producer markets or to consumer markets, while intermediaries are precluded. At the same time, a large share of reduced transaction costs is due to transport costs: there appears to be a huge response from the trading sector. Empirical investigations based on models of behavior of intermediaries find evidence for non-competitive trader behavior (Atkin and Donaldson, 2015; Zant, 2022). Pass-through rates between source and destination markets in Mozambique – an indicator of the competitiveness of trade – tend to be well below 1, and intermediaries are shown to capture sizable surpluses from trade (Zant, 2022). These issues suggest scope for further investigations into the mechanisms underlying the responses by intermediaries.

7. Conclusion and policy implications

This study empirically investigates the impact of the mobile phone roll-out in Mozambique on price dispersion and transport costs. My estimates indicate a 9 % to 15 % decrease in price dispersion, implying that the maize market becomes more efficient as a result of the introduction of mobile phones. The evidence indicates that a large part of this reduction, between 70 % and 80 %, can be attributed to a reduction in transport costs. I verify that these estimates are robust by checking the parallel trend assumption underlying the TWFE approach, and by

[30] The estimated impact on price dispersion range from −467 to −1229 (see Table 1), but is close to −800 with the most preferred sample (Table 1, column 4). I have checked whether the constrained estimation results are robust by employing several sizes of impact within this range.

[31] This robustness check follows up on a comment of a reviewer that the restriction does not hold when there are missing observations. The threshold number (20) is arbitrary: estimations generate similar outcomes for alternative thresholds.

employing propensity score matching to control for possible selection bias. Additionally, I discuss the plausibility of alternative explanations and the relevance of potential threats to identification. The evidence further indicates that the reduction in price dispersion comes about primarily in the form of lower prices in destination markets and, at most, mildly in the form of higher prices in source markets. I find that prices in destination markets fall by 11 %-17 % and, if prices in source markets change at all, they increase by less than 3 %. Hence, the benefits of improved market efficiency are biased towards consumers markets, while market prices in source areas appear unaffected.

These results have several policy implications. The measured impact of mobile phones on price dispersion combined with the large share of this impact that can be attributed to transport costs points at how improvements of market efficiency come about. Apart from conventional investment in transport infrastructure, like roads and bridges, investments in information infrastructure (establishing formal markets and commodity exchanges, collecting and disseminating price information, supporting investments in communication infrastructure) are likely to further improve market efficiency. Nevertheless, these improvements manifest themselves primarily at the market level in the trading business. Although, high transaction costs are a major hurdle for poor agricultural households to access markets and realise higher prices for agricultural output, the improvement in efficiency is mainly accounted for by reductions in transport costs and changes in the transport sector. My results point at important distributional implications from reduction in transaction costs. The evidence indicates that source markets or source areas capture very modest benefits from the introduction of mobile phones: the bulk of the benefits flow to destination markets in urban and coastal areas. The distributional outcomes are similar to the distributional outcomes of agricultural research and development, and fuel price increases.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2023.102423.

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