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Mobile Phones and Mozambique Farmers: Less Asymmetric Information and More Trader Competition?

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Wouter Zant*

Abstract

We measure the impact of search costs on farmers' and traders' transaction prices in Mozambique by investigating to what extent the introduction of mobile phones has affected the margin between recorded maize producer and retail market prices, and by exploring if producers or traders benefit from possible margin changes. Estimations are based on weekly producer and retail market prices of white maize grain, from July 1997 to December 2009, for 15 major producer markets in Mozambique. We find a margin increase that varies from 4.5% to 9.6%, supporting a bias of benefits of mobile phones towards maize traders and hence not less asymmetric information and increased trader competition, but rather the reverse. Impacts on producer and market prices independently vary, but confirm the margin results. Estimation results are robust for non-random rollout of the mobile phone network and various other threats.

JEL code: O13, O33, Q11, Q13

Key words: search costs, transport costs, mobile phones, agricultural markets, maize prices, Mozambique, sub-Saharan Africa

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Introduction

Information on markets prices is essential for performing well in transactions in agricultural commodity chains. Major changes in information infrastructure are therefore expected to have implications for behaviour and transactions of agents operating in these chains. The importance of price information is widely documented, both theoretically and empirically. In economic theory the role of information in economics has a very long history, dating back to the 1960s (see for example Stigler, 1961 and Akerlof 1978 for seminal articles). For the specific setting of the current study we make use of a recent article from Jensen (2010), who builds on this theory and develops a framework for transactions between farmers and traders in a developing country context¹. This framework suggests asymmetric information and increased trader competition as mechanisms to explain how a reduction in search costs and improved information affect behaviour.

The theoretical work is accompanied by a growing body of empirical studies, on the impact of mobile phones or related sources of information. Jensen (2007) makes use of micro level survey data to show that price dispersion on fish markets in Kerala, India substantially decreased after the introduction of mobile phones. Also fishermen's profits and consumer welfare are claimed to increase. Easy and timely access to information is further shown to prevent waste, inefficiency and spoilage of production of perishable crops (see also Muto and Yamano, 2009). Muto and Yamano (2009) investigate marketing costs of maize and bananas during the introduction of 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. Svensson and Yanagizawa (2009) examine the introduction of a Market Information Service in Uganda, which disseminates weekly price information of

¹ Similar studies along these lines are Courtois and Subervie (2015) and Mitra et al. (2018).

agricultural crops through local FM radio stations. The MIS introduction is considered a natural experiment: on the basis of a difference-in-difference approach of participating and non-participating districts, and households with and without access to radio it is shown that MIS use is associated with 15% higher farm-gate prices and, thus, evidence of an improved ability of farmers to bargain for prices. In a study on the soy market in the Indian state of Madhya Pradesh, Goyal (2010) investigates the impact of a direct marketing channel for farmers through internet kiosks, offering price information, warehousing, quality testing and direct sales to the private sector end-user (and thereby bypassing intermediary traders): soybean prices increased, price dispersion decreased and area under soy cultivation increased. Fafchamps and Minten (2012) estimate benefits for farmers of SMS based agricultural information in Maharashtra, India, using a randomized controlled trial. The information (Reuters Market Light) 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 results are in line with the limited commercial take-up of the information service. A comparative advantage in transport is suggested as an explanation why benefits accrue in the first place to traders and not to producers. Tadesse and Bahiigwa (2015) explore impact of mobile phones on marketing decisions and prices, on the basis of a 2012 household survey of central and southern Ethiopian rural households. Despite widespread ownership of mobile phones among farmers, impacts are mixed and not strong enough to believe that mobile phones are helping farmers' marketing decisions. They attribute this finding to a lack of relevant information that can be accessed by mobile phones. Courtois and Subervie (2015) employ a two period bargaining game between farmers and traders to explain the impact of improved information. Based on survey data, they measure empirically the impact of a market information system in a northern region of Ghana, on maize and groundnuts farm gate prices. They find that farmers participating in the MIS

program received respectively a 10% and 7% higher price compared to if these farmers had not participated. Aker and Skoll (2016) document results of a randomized control trial of access to ICT and capacity to use ICT, among 1044 rural households in Niger. They find a more diverse basket of crops, particularly cash crops by women, but no support for higher crop revenues or increased prices. Other market failures need to be addressed to improve farmers' welfare.

Beyond empirical work on the impact of information infrastructure, there are several extremely insightful articles on sub-Saharan African trade, how trade affects prices and the relationship between farmers and traders (see for example Minten and Kyle, 1999; Fafchamps, Gabre-Madhin and Minten, 2005; Jacoby and Minten, 2009; and Fafchamps and Vargas Hill, 2005). An extensive study by Fafchamps, Gabre-Madhin and Minten (2005), based on trader surveys in Benin, Madagascar, and Malawi reveals many interesting stylized facts on the trading business in sub-Saharan Africa: dispersion of the size distribution of trader businesses and the prevalence of many small scale businesses suggest constant returns to scale in trade; around 75% of all traders buy directly from farmers and sell as a retailer; by far the largest component of costs of domestic trade is transport costs, with an estimated share of 48 to 57% of total transaction costs; average distance between purchase location and sale location of maize transactions is around 55km with a maximum of 200km; traders on average supply 96% of the working capital of their trading business themselves and around 88% of all traders are 100% funded with own capital; and the average (median) number of days between purchase and sale is nearly 8 days (3 days), with around 45% of the transactions completed within two days and less than 10% in more than 14 days.

In the current exercise the farmers' decision to sell at the farm gate or on the market plays a major role. Fafchamps and Vargas Hill (2005) investigate this issue on the basis of survey data of Ugandan coffee farmers. In choosing between selling to an itinerant trader at

the farm gate or carrying output to the nearest market town and sell on the market, they find that farm households are more likely to sell to the market when the quantity sold is large and the market is close by, and wealthy farmers are more likely to travel to distant markets.

What is our contribution to this literature? In this study we analyse the income effects of mobile phones for farmers and traders, and implement this, primarily, on the basis of farm gate and market prices, recorded for the same market. Most, if not all, assessments of impacts on farmers are exclusively based on household survey data (Muto and Yamano, 2009; Fafchamps and Minten, 2012; Tadesse and Bahiigwa, 2015). Alternatively, most price based assessments are nearly exclusively looking at price dispersion between markets, spatial arbitrage and market efficiency (Aker, 2010; Aker and Fafchamps, 2014; Zant, 2017a), rather than returns of agents in the commodity chain. We analyse the impact of mobile phones on farmer producer prices, market prices and margins of traders, on the basis of market data. The combination of producer prices with market prices allows – in contrast with survey based empirical work – to highlight the interaction between farmer and trader and make evidence-based claims how shocks affect both farmer and trader. The exercise comes closest to Mitra et al. (2018) and Courtois and Subervie (2015). Next, we propose several ways to complement and strengthen the obtained results (verification of results with household survey data, behavioural changes of farmers in production and marketing, identifying changes in the outside options of farmers and traders, characterizing the farmer-trader bargaining, and identifying constraints for farmers to benefit from mobile phones).

The remainder of this study is organised as follows. In Section 2 we present a simple framework that explains how information affects behaviour. In Section 3 we discuss the Mozambique maize market, maize prices, margins between farm gate and market prices, and the mobile phone rollout. In Section 4 we document data and data sources, and elaborate the empirical strategy. In Section 5 we present the empirical estimations and robustness checks. In

Section 6 we discuss other potential threats and alternative explanations. In Section 7 we elaborate on potential contributions of (household or trader) survey data and outline several possibilities to verify and explain obtained results, and to enrich insights. Finally, we summarize and conclude this study in Section 8.

2. Conceptual Framework and Model

Conceptual framework: behaviour of traders vis-à-vis producers and on the market

With respect to commodity chain and transactions, we consider the following set-up. There are two agents, farmers and traders, we distinguish three locations for transactions, the farm, the home market and the distant market, and we consider a widely traded non-perishable agricultural commodity². The distant market is the domain of the itinerant trader³: this trader earns an income from price differences between geographically dispersed markets, connecting excess supply with excess demand. The associated spatial arbitrage is not the topic of the current paper, but analyzed elsewhere (see Zant, 1017a). Traders purchase from farmers at producer prices (pf), and sell on the market, either on the home or distant market. We assume that farmers sell, primarily, at the farm-gate and the farmer earns the producer price (pf). The farmer may also sell his maize production on the home market. In that case the farmer engages in trading activities and the farmer earns the market price (pm). Since we only have price data, we cannot observe if and to what extent farmers operate as traders and sell on the (home) market or, alternatively, sell at the farm gate (see Fafchamps and Vargas-Hill, 2005 for an analysis based of survey data). The possibility that farmers engage in

² The various dimensions of the set-up are not trivial, as these make a distinctive empirical analysis. In this connection it is an open question whether comparisons of, for example, south Indian fisherman (Jensen, 2007: transport by sea/boat, over less than 150km, perishable crop, no seasonality) and itinerant grain traders in Niger (Aker, 2010: transport by road/truck over up to 1200km, storable crop, strong seasonality) are useful.

³ We make the assumption (or claim) that farmers are not involved in spatial arbitrage, but only decide if they sell their output at the farm-gate or on the nearby market. This is supported by the organization of the trading business (see Fafchamps et al. 2005). Some authors also find no arbitrage between markets by farmers (for example Fafchamps and Aker, 2016). Alternatively, one could explain arbitrage by farmers as typical trading activities (rather farming activities).

trading activities and transport and sell their produce on the market does play a role in the farmer-trader bargaining process (see further in this section). The analysis in the current study focuses on the impact of a change in information infrastructure (mobile phones), and thereby of a change of search costs, on the difference between price received by farmers at the farm-gate (the producer price, p_f) and the price earned from selling on the home market (the market price, p_m).

We assume that traders behave as monopsonists in their transactions with farmers. Consequently, traders are price setters and have buying power when purchasing maize from farmers: they can reduce prices and influence purchased quantities. Buying power of traders arises by the circumstance that most farmers do not have an alternative outlet for selling their maize and lack the superior information about the market that traders have. This set-up is similar to the general case – also beyond developing countries – where food retailers have power when purchasing supplies from a wide range of agricultural suppliers. The buying power enables traders to keep the transaction price low. The introduction of mobile phone technology affects search costs and asymmetric information. The impact on transaction prices depends on the degree of market power and the slopes of the demand and supply curve. In the case of traders with much buying power transaction prices with farmers will only be marginally affected. Given profitable margins, traders' demand for maize will also be highly elastic.

Once traders bring their maize purchased from farmers to the market, traders are in a completely different position. Markets are assumed to be competitive. Mainly due to the number of agents on both sides of the market, traders have negligible power to set transaction prices. If announced prices are too low (too high), sellers (buyers) will simply look further to find a more attractive transaction. Therefore, that traders take market prices as given.

How does the introduction of mobile phones – a change in search costs – affect the transactions of farmers and traders? The channels of impact run through the change in asymmetric information between farmers and traders, and the increased activities of traders due to lower search costs, leading to higher competition between traders, and higher prices offered to farmers (see Jensen, 2010). Farmers may sell at the farm-gate or on the market and their decision is driven by expected (market) prices. If announced purchase prices of traders at the farm-gate are too low, farmers may decide to transport their production to the market themselves. In view of this alternative traders will align their purchase price to farmers' expected prices. With frequent exposure to the market, traders commonly have an information advantage vis-à-vis farmers in the bargaining process: due to asymmetric information, gains of transactions are likely to be biased towards traders. The introduction of mobile phones allows farmers to obtain up-to-date information on market prices and timely adjust expected prices. Conversely, traders will anticipate on this change and align their price offers to the revised farmers' expected prices. Hence, the introduction of mobile phones can be expected to shift the balance of the asymmetric information in the bargaining process in favor of farmers.

The conceptual framework employed in this study is equivalent to game theoretic approach adopted in Courtois and Subervie (2015). Courtois and Subervie (2015) develop a simple but elegant two period bargaining game between a farmer and a trader, under asymmetric information, with the trader fully informed, and under full information, with both farmer and trader fully informed. Farmers utility is determined by pay-offs which is the selling price minus their reservation price and possible transportation costs, they discount second period payoffs, they have a reservation price determined by production costs, and they incur (farmers') transportation costs if they decide to bring their produce to the market. Traders utility is determined by payoffs, which is the market price, minus the cost of

purchasing from the farmer – the farm-gate price – and the traders' transportation cost. The game is solved by backward induction. From comparison of the asymmetric information and full information game, the authors derive that an equilibrium exists in both regimes, that asymmetric information may lead to a negotiation failure, while this is avoided under full information, and full information leads to a larger transaction price for farmers in a high price state and a lower price for farmers in a low price state.

Beyond the farmer-trader interaction, changes in information infrastructure is also affecting the trading sector per se. Traders who purchase output from farmers face three costs: the purchasing price, transport costs and search costs. Search costs arise by collecting information on market prices on different markets, and by traveling across agricultural areas and searching for profitable purchases of farmers' output. Introduction of mobile phones will greatly improve the efficiency of this search process, and, consequently, search costs will decrease. This reduction in search costs allows traders to extend activities and travel further thereby increasing total transport costs, but decreasing per unit transport cost. As, at the same time, other traders will do the same competition is likely to increase at the margin. Increased competition between traders may also lead to higher prices offered to farmers.

Improved information further leads to additional efficiency gains, through several other channels (Jensen, 2010): improved profitability of crop cultivation may trigger increases in output and changes in crop composition. Improved information will affect transport and per unit transport costs through increased arbitrage. Lower per unit transport costs will increase competition between traders, and this may further lead to gains for farmers. And, finally, increased arbitrage will dampen price volatility: with increased flows from excess supply to excess demand areas, on average, price volatility will be reduced.

3. Mozambique Maize Production, Maize Prices and Mobile Phone Rollout

Maize production

Maize is the most important staple food of Mozambique: it is 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 together (Tschirley et al., 2006). On the consumption side the calorie share of maize in the Mozambique diet ranges from 25% to 39%, corresponding with a per capita (annual) consumption of 60 to 85 kg. However, particularly in the south, and in the Maputo region, the maize share in the consumption diet is lower due to substitution with rice (Tschirley et al., 2006).

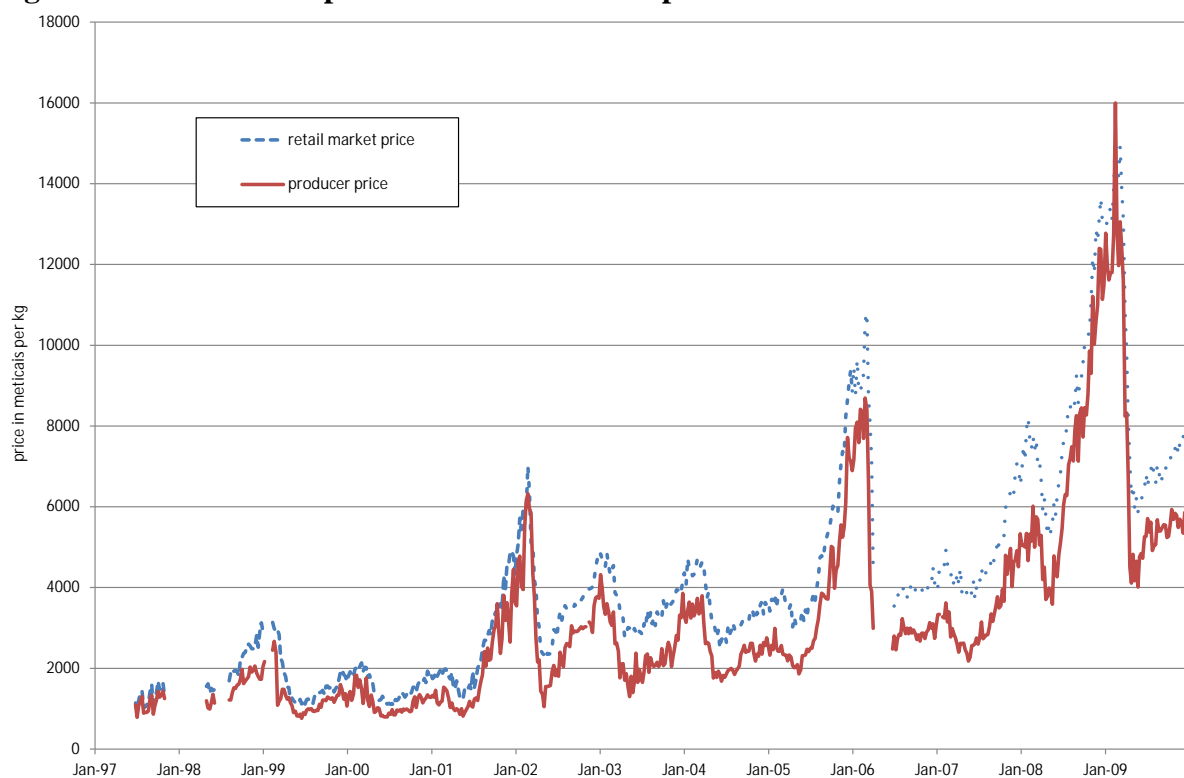
Domestic production of maize is concentrated in the central and northern part of Mozambique (for a map of Mozambique, see Appendix, Figure A1). The Northern provinces Niassa, Cabo Delgado, and Nampula have better rainfall distribution and better soil fertility, while the Southern region has unfavourable weather conditions and suffers from occasional pests (Abdula, 2005; and Appendix, Figure A3). Most agricultural production in Mozambique is rain-fed. Drought and also flooding cause drops in production, and related hikes in prices. In the 1999-2000 crop season, maize production declined 18 percent, primarily due to floods that devastated large areas of the centre and south of the country (Abdula, 2005). Due to subsistence farming only around 30% of total production is sold on the market. Major production, assembly and wholesale markets in the central region are Manica, Chimoio and Gorongosa, and, in the north, Cuamba, Mocuba and Montepuez (see Appendix, Figure A1).

Producer prices and retail market maize prices

Price developments over time (see Figure 1) reflect the rain-fed character of agriculture. Prices peaked in 2002 and 2006 due to droughts. Note, however, that the 2009 peak was

triggered by a surge in food prices world-wide⁴. Moreover, there is strong seasonality in maize prices: prices start to rise gradually from July-August, to reach a maximum around March, and to drop drastically from March to June. The degree of price seasonality (see Appendix, Figure A4) is large with lean season prices twice as high compared to post-harvesting months, corresponding with observed seasonality in staple food prices in other sub-Saharan countries (see Kaminski et al., 2016). Seasonality in prices makes timing of transactions critical: postponing maize sales, for example, with two months may lead to an increase of proceeds of 20% to 30%⁵. Strong seasonality in prices also should be a major concern for researchers using prices or unit values extracted from survey data.

Figure 1 **Producer prices and retail market prices of maize**

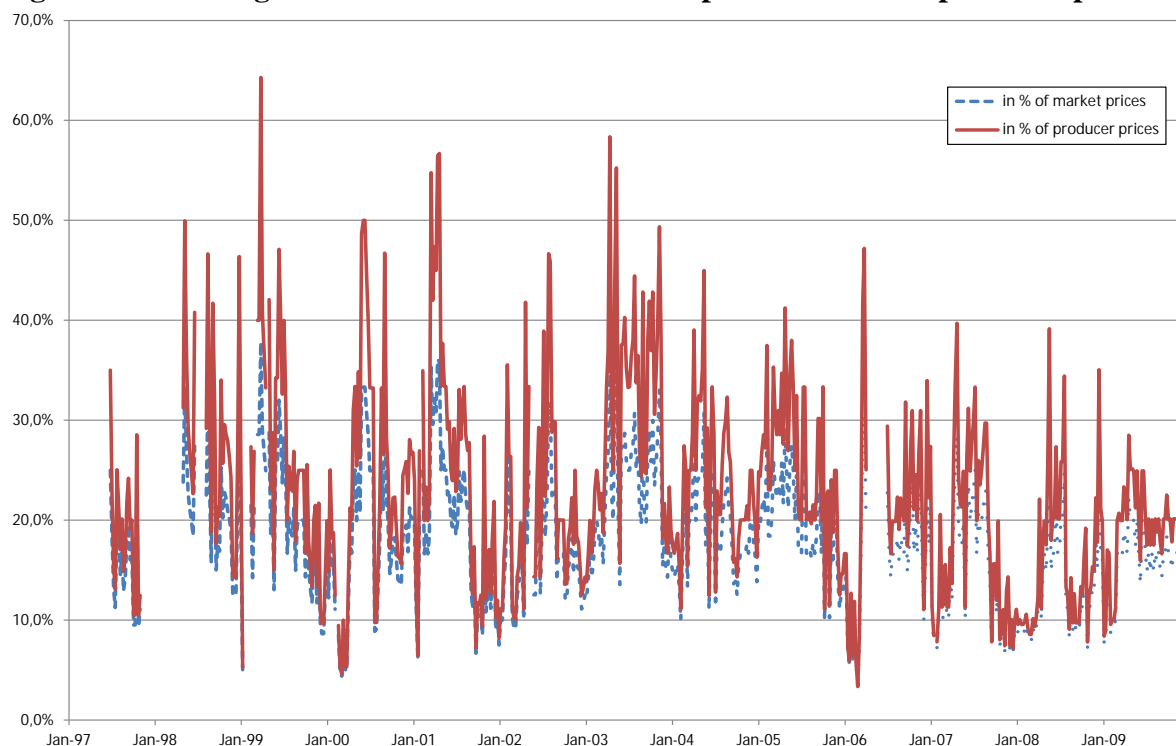


Source: Authors' calculations based on Sistema de Informação de Mercados Agrícolas de Moçambique data.

⁴ The world-wide price surge in food prices was due to several events among others high energy prices, regional droughts in producing areas, WTO, and shifts to trade in commodities in the aftermath of the financial crisis.

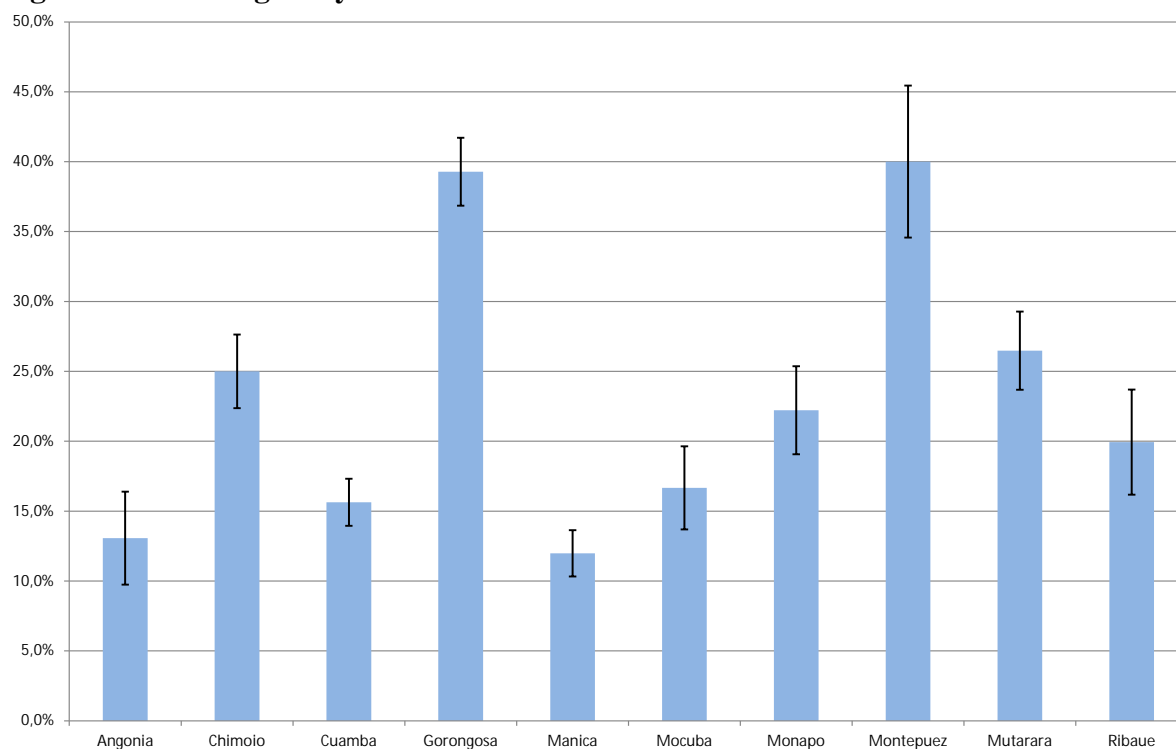
⁵ Improved information on market prices may, therefore, also affect storage behavior of farmers.

Figure 2 Margin between maize retail market prices and maize producer prices



Source: Authors' calculations based on Sistema de Informação de Mercados Agrícolas de Moçambique data.
Note: The figure shows the development over time of the margin (the market price minus producer price) expressed in percentage of either market or producer prices, and averaged over markets.

Figure 3 Margins by markets



Source: Authors' calculations based on Sistema de Informação de Mercados Agrícolas de Moçambique data.
(the figure shows only markets with more than 100 observations)

By way of describing the data, we show margins over time, averaged over markets (Figure 2) and by market, averaged over time (Figure 3). The over-time presentation indicates stationarity of the series, around a, possibly varying, non-negative mean (note that, due to missing observations, the figure averages over different samples of markets). The by-market data support fixed effects by market: margins are clearly an order of magnitude different between markets. This most likely reflects local circumstances like the distance from the market to the major producer areas, the geographical dispersion of farmers, the number of traders and the degree of competition between traders active in the market.

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. The number of mobile phone customers (subscriptions) in Mozambique increased from 51,065 in 2000 to 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. Compared to high income country standards still a modest share, but drastically higher than 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 cost of setting up a mobile phone network (vis-à-vis a landline network), the low prices of mobile phones, the low cost of mobile phone use, the widespread promotion of the pre-payment system (which solved the cashing problem, a key problem with land lines), and the distribution of pre-paid cards for very small amounts. Despite the reasonably low costs of mobile phones and mobile phone use, it is likely that use and access to mobile phone services is still biased against the poor.

The rollout of the mobile phone network in Mozambique started in 1997. During the first three years (1997-1999) mobile phone towers were installed exclusively in the densely populated and high income Maputo and Matola area, in order to guarantee returns to

investment in the built up of the mobile phone network. However, after a period of around ten years the network has extended to most major cities and towns, roughly following the existing trunk road network (see map with rollout in the Appendix). Roll-out data also reveal that rural areas in general, and the province of Niassa in the north in particular, are underserved, both in terms of area and population.

4. Data and Empirical Strategy

Data, data sources and data availability

The data on the rollout 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 first year of operation⁶. The rollout data that we have stretch from 1997 to 2009⁷. We employ a range of 35 km around the mobile phone tower (as the crow flies) to identify markets that have mobile phone facilities⁸.

Maize prices are from the weekly publication Quente-Quente published by Sistema de Informação de Mercados Agrícolas de Moçambique (SIMA; www.masa.gov.mz/sima). SIMA, which started as a USAID / Michigan State University funded initiative, weekly distributes price bulletins, by email (covering amongst others farmer organizations, traders), by SIMA's provincial offices (that further reproduce and disseminate information), through the Ministry of Commerce that uses the information in their own bulletins, and through

⁶ Cell phone roll-out data were made kindly made available by Jenny Aker.

⁷ It is unlikely that further extension of the mobile phone network has stopped in 2009. However, with the limited number of markets (towns and cities) identified in the empirical estimations the roll-out in our data set is completed already in 2006.

⁸ 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 (for example 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).

broadcasts on the national radio and television news (to whom SIMA contractually offers weekly input to market programs). Traders interviews confirm the effectiveness of the SIMA price information⁹.

For the current study we use in particular the weekly producer prices and retail market prices (respectively Quadro 2: Preço e Mudança Percentual a Nível Produtor (Mts/Kg) and Quadro 3, Preço e Mudança Percentual a Nível de Mercado Retalhista (Mts/kg)) of white maize grain (grão de milho branco). The price data are collected by interviewing each Monday three randomly selected traders in each market and for each commodity. Producer prices are recorded for 15 markets, while retail market prices are recorded for a larger set of 27 markets¹⁰. We assume that the set of markets for which producer prices are recorded, are representative for Mozambique maize grain farm-gate prices, refer to these prices as producer prices, and focus, in the first place, on market-date combinations that have both producer prices and retail markets prices. We use data for the period from July 1997 to December 2009: this period covers the effective period of the roll-out of mobile phone infrastructure, with additionally a few years before and after, with no and with full access¹¹ to mobile phones.

⁹ See “In Mozambique, Market Information publishes its 500th weekly bulletin, a Cause for Celebration”, February 2006 posted on the internet (www.masa.gov.mz/sima/).

¹⁰ *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.* Markets for which producer price are recorded are in italics. A map in the Appendix (Figure A1) shows the locations of these markets in Mozambique.

¹¹ *Full access* in this context means that all markets identified in this study have access to mobile phone technology.

Table 1 **Availability of weekly price data by market**

Market	north / south of Zambezi	1 farmgate price	2 market price	3 combined	4 missing in %	5 cell (in% of 3)
Alto Molocue	N	27	198	24	96,3%	0%
Angoche	N	49	127	45	93,1%	0%
Angonia	N	322	346	290	55,6%	67.2%
Cuamba	N	299	338	284	56,5%	94.7%
Mocuba	N	169	296	164	74,9%	13.4%
Monapo	N	146	157	132	79,8%	0%
Montepuez	N	180	231	164	74,9%	75.6%
Mutarara	N	183	360	172	73,7%	14.0%
Ribaue	N	159	260	119	81,8%	36.1%
Chimoio	S	535	568	530	18,8%	90.9%
Chokwe	S	20	449	17	97,4%	23.5%
Gorongosa	S	344	350	339	48,1%	99.4%
Manica	S	545	559	499	23,6%	82.8%
Massinga	S	81	413	77	88,2%	0%
Nhamathanda	S	70	70	66	89,9%	100%

Note: The data span from July 1997 to December 2009. Column 3, *combined*, shows the number of market-date observations with both producer and market prices, and with market prices equal or above producer prices. ($pf > 0$, $pm > 0$ and $pm \geq pf$)¹². Column 4, *missings in %*, expresses column 3 in terms of the maximum potentially available observations for each market (=total number of weeks). Column 5, *cell*, shows the share of market-date observations with access to cell phones.

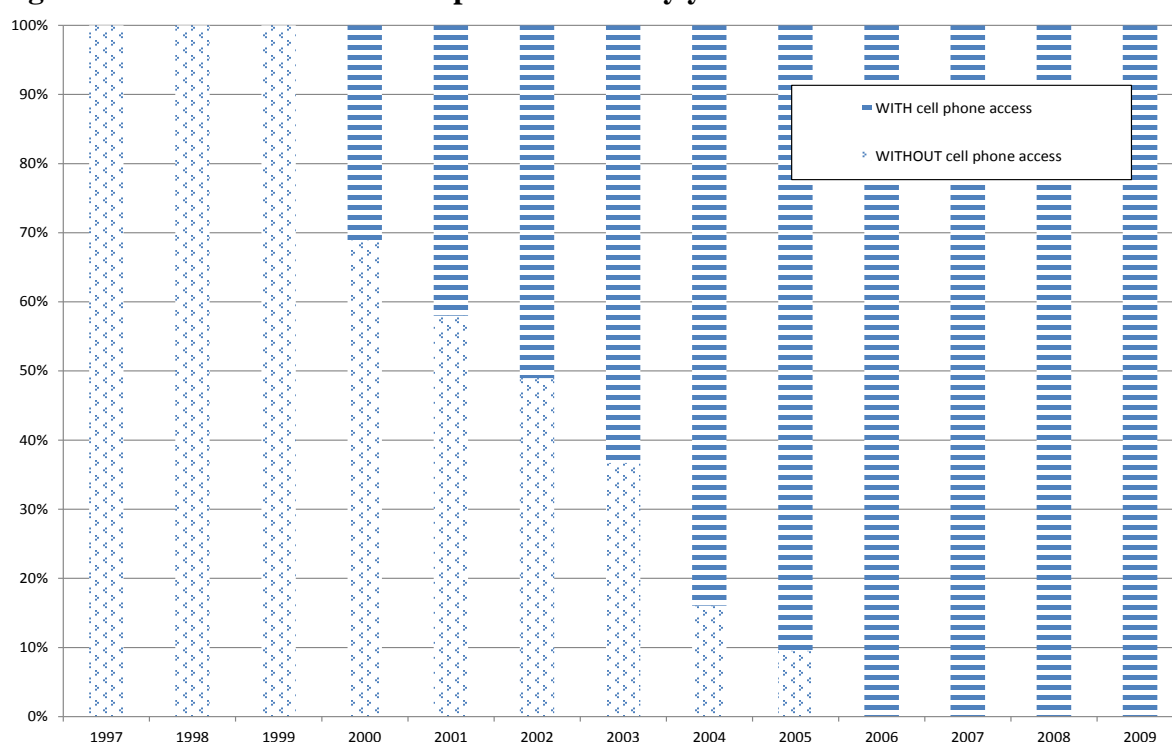
Unfortunately, there are missing observations in the price data. Table 1 summarizes the availability of price data by market. At first glance, the reported numbers of missings in terms of the potential number of data (Table 1, column 4) are not very assuring: only in the case of Chimoio and Manica a reasonable percentage of around 20% missings is realised. However, missing data are quite common in agricultural markets. During many parts of the season there are simply no transactions taking place. SIMA staff confirms that missing data are the result of no transactions in the market¹³. Most farm households sell maize directly after harvest, during a restricted time span, often not longer than two or three months. From this perspective around 80% of missings is normal, while substantially less than 80% missings is

¹² In the calculation of the margin we have assumed that observations with a producer price above the market price, reflect errors in data collection and compilation, or errors due to inconsistencies in aggregation or sequencing of prices over the week. For this reason these observations – around 3.5% of the observations and, hence, not a serious concern – are therefore omitted. Alternatively we may consider these data as real, but only relevant for trade between markets (spatial arbitrage) and thereby not relevant for the current exercise. Producer and market prices' estimations are restricted to samples for which a margin observation is available.

¹³ More specifically we attribute missings to lack of supply. Given the nature of the price data, we cannot interpret missings as negotiation failures (see Courtois and Subervie, 2015), also because we cannot separate out missings due to lack of supply.

extraordinary. Moreover, we may qualify markets with substantially more than 80% missings as markets with producer activity only during a limited number of seasons (Alto Molocue, Angoche, Chokwe, Nhamatanda). Hence, as the prevalence of missing observations is not correlated with access to mobile phones, but driven by completely different dynamics, we conclude that sample selection due to missing observations should not be a major concern. However, missing observations do create other serious issues (see following sections).

Figure 4 Price data and cell phone rollout by year



Source: Authors' calculations based on data from Sistema de Informação de Mercados Agrícolas de Moçambique and the Ministry of Transport and Communication of Mozambique.

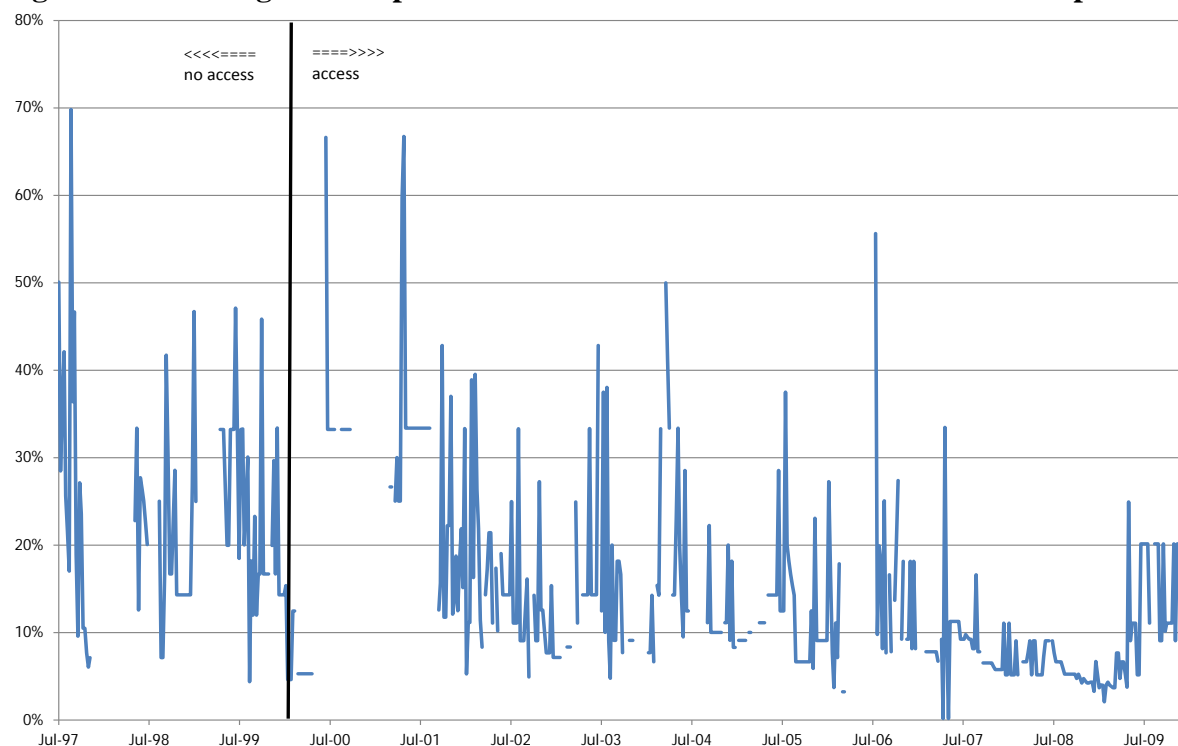
Table 2 Price data by cell phone access and year (numbers)

	Year	97	98	99	00	01	02	03	04	05	06	07	08	09
Without	by yr	65	117	193	144	127	92	93	42	26	0	0	0	0
	cum.	65	182	375	519	646	738	831	873	899	899	899	899	899
With	by yr	0	0	0	65	89	99	162	235	235	190	254	281	299
	cum.	0	0	0	65	154	253	415	650	885	1075	1329	1610	1909
Total		65	117	193	209	216	191	255	277	261	190	254	281	299

Source: Authors' calculations based on data from Sistema de Informação de Mercados Agrícolas de Moçambique and the Ministry of Transport and Communication of Mozambique.

Note: The table only reports the weekly observations by market with both producer ($pf > 0$) and retail market prices ($pm > 0$), where $pm \geq pf$.

Figure 5 Margin for a specific market* : before and after access to mobile phones



Source: Authors' calculations based on data from Sistema de Informação de Mercados Agrícolas de Moçambique and the Ministry of Transport and Communication of Mozambique.

Note: The figure shows the market price minus producer price as a percentage of producer price for Manica.

The combination of price data and mobile phone rollout, shown in Figure 4 and Table 2, confirms that the available price and margin data are nicely distributed, before, during and after the rollout of the mobile phone network. The rollout of mobile phone technology in our sample of markets starts in the year 2000 and is completed in the year 2005. Also, it is clear that balance between observations with and without access to mobile phone technology is realised already in 2005-2006: hence, rather than using the entire sample from July 1997 to December 2009, it appears justified to mitigate the influence of potential confounders and run the estimations for a sample that is restricted in time. Such estimations improve results in some specifications considerably (see sensitivity analyses and robustness checks).

It is tempting to illustrate impact by simply plotting averages prices or margins before and after the introduction of mobile phone technology (see e.g. Jensen, 2007; Steinwender, 2018). Unfortunately this is not a straightforward exercise: prices and margins differ

significantly by market, data are incomplete making comparisons unbalanced, strong seasonality further complicates things, and we lack a clear deflator that accounts for variation over time and over space (see also section below). If we restrict the before and after comparison to specific markets (thereby accounting for market fixed effects) and deflate with the uniform country wide CPI, another problem pops up: the number of observations before and after, for specific markets is often unbalanced, and occasionally small (or even zero). A graphical presentation for a specific market, shown in Figure 5, seems to suggest that both level and volatility have decreased slightly after access to mobile phone technology, but this is, honestly, not well pronounced¹⁴.

Table 3 Before and after: averages and differences

market: Angonia	before access to mobile phones	after access to mobile phones	Difference
number of observations	92 (32.2%)	194 (67.8%)	
average of producer price	7162.6 (408.5)	6228.8 (219.9)	-933.7
average market price	8016.0 (435.7)	7227.0 (256.5)	-789.0
average margin	0.139 (0.0105)	0.166 (0.0073)	0.027
variance of margin	0.0101 (0.0049)	0.0103 (0.0037)	0.000205
market: Montepuez	before access to mobile phones	after access to mobile phones	Difference
number of observations	40 (27.6%)	105 (72.4%)	
average of producer price	3266.0 (192.7)	4605.2 (139.1)	1339.2
average market price	4335.8 (296.0)	6548.6 (155.3)	2213.8
average margin	0.312 (0.0275)	0.446 (0.0207)	0.134
variance of margin	0.0303 (0.0124)	0.0450 (0.0055)	0.014749
market: Ribaue	before access to mobile phones	after access to mobile phones	Difference
number of observations	67 (61.5%)	42 (38.5%)	
average of producer price	3587.8 (152.5)	5155.1 (322.4)	1567.3
average market price	4279.5 (185.4)	6682.8 (380.0)	2403.3
average margin	0.198 (0.0194)	0.320 (0.0260)	0.123
variance of margin	0.0253 (0.0052)	0.0285 (0.0058)	0.003189

Note: the weekly variance of the margin is calculated as: $\text{var}(\text{margin}_t)_z = n_z / (n_z - 1) [\text{margin}_{tz} - \text{average}(\text{margin}_{tz})]^2$, where z is either before or after access to mobile phones (see e.g. Steinwender, 2018).

We have further selected three markets, shown in Table 3, with a reasonable number of observations before and after, and also as balanced as feasible. All three markets show an

¹⁴ The figure is remote from the impressive ‘before and after’ figures in Jensen (2007) and Steinwender (2018). Note, however, that our data are much more problematic, due to seasonality and missings (but also much more relevant!) and cover a longer period.

increase in the average margin. In two of the three markets this increase is the result of a larger increase in market prices (relative to producer prices), in one of a higher decrease of producer price (relative to market prices). From the preceding descriptive exercises we conclude that a comprehensive estimation strategy is needed to disentangle various factors.

A few other variables are used in the empirical work, primarily for estimations with covariates, to estimate the propensity score and as instruments in IV/2SLS estimation. Poverty head count data are based on household surveys and sourced from van de Boom (2010) and Alfani et al. (2012). Available poverty head count data are by province and for three dates (January 1998, January 2003 and January 2009): observations by province are attributed to markets, and monthly values are constructed by interpolation. Population data, both by province and by city or town, are from three censuses (1997, 2007, 2016) from the Instituto Nacional de Estatística Moçambique. Population data for intermediate months and years are constructed by interpolation. Network density is a constructed index that is calculated as the sum of population of all markets over road distance to these markets ($\text{network density}_i = \sum_j (\text{population}_j / \text{road distance}_{ij})$ where i and j are markets, and $i \neq j$). Distance, both road distance and Euclidian distance (“as the crow flies”) in kilometres is obtained from GoogleMaps, accessed at the time of implementing this study (2017)¹⁵. The variable distance to large cities is the closest road distance from a specific market to either Maputo, Beira or Nampula. Finally, we have used the national monthly consumer prices index for Mozambique, which is taken from the International Financial Statistics of the IMF.

Empirical Strategy

In order to compare markets with and without mobile phone coverage, we estimate – as a start – the following specification with OLS:

¹⁵ By implication, possible changes in road infrastructure during the period of study (July 1997 – December 2009) are not properly accounted for.

$$(1) \quad y_{jt} = \beta_0 + \beta_1 \text{phone}_{jt} + \mathbf{X}_{jt}\gamma + \eta_j + \theta_t + \varphi_{jm} + \varepsilon_{jt}$$

where y_{jt} is either margin, producer price or market price in market j and in period t , phone_{jt} is a binary variable equal to 1 in period t if markets j has mobile phone facilities, and zero otherwise. The vector \mathbf{X}_{jt} represents variables that influence margins and prices, such as variations in supply conditions like drought and flooding and variations differences in demand like population size and income. Parameters η_j and θ_t represent market and time fixed effects, φ_{jm} represents seasonality in market j , and takes the value 1 for each month (January, February, etc) and zero elsewhere, and ε_{jt} is an error term with zero mean and constant variance. Since we have included time and market fixed effects, estimation of equation (1) is equivalent to a difference-in-difference estimation (DiD). The parameter of interest is β_1 which measures the impact of mobile phones on either price margins, producer price or market price. All variables other than indicator variables are in natural logarithms.

For the estimation of equation (1) to generate valid estimates of the impact of mobile phone on price margin and prices, it is required that both observations of markets with and without access to cell phones are random samples. Since our data are non-experimental, this is unlikely to be the case: the description of the rollout of mobile phone technology clearly reveals several drivers that guided investments in the expansion of the network. To address potential selection bias that arises because of this, we employ standard techniques for non-experimental data, notably propensity score matching (PSM) and instrumental variables (IV-2SLS).

The first step of PSM is to model the probability (not) to have access to mobile phones, the propensity score: observable determinants of the rollout of the mobile phone network are exploited to establish a well performing probability model of access to mobile phones. The propensity score is assumed to be explained by the poverty head count, population of the city or town, network density and the distance to large cities. In the second

step a matching algorithm is employed to select observations for comparison, with a similar propensity score, both with and without access to mobile phones. Given the sufficient availability of control observations we use Kernel Matching as a matching algorithm, to match treatment and control observations. Kernel Matching is a non-parametric estimator that uses a weighted average of all control group observations to construct the counterfactual outcome. Weights depend on the distance between each observation from the control group and the treatment observation for which the counterfactual is estimated, with higher weights on observations close in terms of propensity score and vv . As more information is used compared to, for example, Nearest Neighbour matching, Kernel Matching results in a lower variance, and, thus, higher precision estimates. The Kernel function is the Epanechnikov kernel. Following accepted practise we use a bandwidth of 0.06.

As matching is based on properties and traits that explain the probability to have access to mobile phone technology, the PSM estimations cannot adequately account for the strong seasonality in prices. As a result matching may join together observations that are different in terms of seasonality. Consequently, we have adjusted price series for seasonality and apply the PSM estimations to the seasonally adjusted series. For the construction of seasonally adjusted prices, we first regress $\ln(p)$ on market, month-year and market-specific seasonal dummies and trends, next, use this estimation to construct a predicted price $\ln(p_{seas})$ and finally, calculate the natural log of the seasonally adjusted prices as $\ln(p) - \ln(p_{seas})$. Applying this procedure, however, introduces a subtle issue of inference: a change in the information infrastructure is also likely to interact with seasonality in prices. Therefore, and ideally, the impact of mobile phones need to be estimated jointly with seasonality. Unfortunately, we are unable to solve this within a matching framework.

Complementary to the Dif-in-Dif and the PSM estimations we have estimated equation (1) with Instrumental Variables / Two Stage Least Squares (IV/2SLS). The mobile

phone variable is instrumented with trend, population, poverty head count, network density and distance to major city, all in natural logarithms. We test whether we can reject the hypothesis of weak instruments and discuss the exclusion restrictions. To assess the quality of the instruments we report the Sargan statistic, an over-identification test of all instruments. Typically values larger than 10 suggest that we may reject the hypothesis of weak instruments. Next, for instruments to satisfy the exclusion restrictions, instruments should be distributed independently of the error process of the estimated equation, but simultaneously (sufficiently) correlated with the included endogenous regressors. The first implies that the instruments affect the outcome variable only through the treatment variable, and not directly. Unfortunately the exclusion restrictions cannot formally be tested: we can only justify these restrictions on economic grounds. Instruments are trend, population, poverty head count, network density and distance to major city. Investment in the mobile phone network is driven by the perspective of making profits with the mobile phone business. Consequently, potential demand (population, income (approximated with the poverty head count), network density) and costs (distance to nearest large city) are major determinants of this activity. These proposed approximations correlate well with the treatment variable (access to mobile phones). Simultaneously, these demand and cost approximations are not likely to be meaningfully correlated with the outcome variable, maize prices or margins. Hence, we claim that the exclusion restrictions for our empirical model are supported by theory and cannot be rejected.

5. Empirical Estimation, Sensitivity Analysis and Robustness Checks

Basic specification

Specification of equation (1), augmented with market specific seasonality, is first estimated with OLS. Following standard practise we are inclined to cluster errors (Bertrand et al.,

2004). However, Abadie et al. (2017) claim that clustering of standard errors by a specific variable is not necessary, if the estimated specification includes fixed effects of that specific variable (in our case the obvious choice is to cluster errors by markets, and we have also included market fixed effects). Hence, we show OLS estimations both with and without clustering of standard errors. Next, we report the matching estimations. We assess the quality of the PSM estimations by discussing if the determinants of the propensity score meet the requirements and how well the propensity score is explained, by considering the matching algorithm and showing if the common support condition is met, and by assessing the quality of the matching outcome on the basis of the standardised bias of covariates (Rosenbaum and Rubin, 1985). Propensity score estimations, common support figures and the standardised bias of covariates are all shown in the appendix. Finally, we report the IV-2SLS estimations. With respect to the IV-2SLS estimations we assume that the exclusion restrictions are satisfied and discuss the quality of instruments.

The results, reported in Table 4, indicate that the margin has increased, from a modest 4.5% to a maximum of 9.6%. This increase is combined with a substantial decrease of both producer and market prices, where the decrease of producer prices is slightly larger. The outcome indicates that the increase in margin is fully captured by traders, and, hence, we conclude that benefits of the introduction of mobile phones are larger for traders. Both PSM and IV-2SLS score well on properties (PSM: propensity score estimation, common support, standardised bias; IV-2SLS: quality of instruments and exclusion restrictions).

Table 4a Impact of mobile phones on prices and margins: full sample, OLS/DiD

dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.096*** (0.011)	0.097*** (0.012)	-0.131*** (0.019)	-0.133*** (0.021)	-0.036** (0.017)	-0.035* (0.019)
Covariates	No	yes	No	Yes	No	yes
clustering of errors	No	No	No	No	No	no
adj R ²	0.4685	0.4911	0.8365	0.8367	0.8395	0.8450
no. of observations	2902	2902	2902	2902	2902	2902
dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.096** (0.043)	0.097** (0.041)	-0.131* (0.068)	-0.133** (0.060)	-0.036 (0.089)	-0.035 (0.076)
Covariates	No	yes	No	Yes	no	yes
clustering of errors	Yes	yes	Yes	Yes	yes	yes
R ²	0.5215	0.5423	0.8526	0.8531	0.8555	0.8606
no. of observations	2902	2902	2902	2902	2902	2902

Note: Maize price data are from July 1997 to December 2009 (source: SIMA). All estimations include market and year-month fixed effects, and control for market specific seasonality. Prices are deflated with the national consumer price index. Covariates are poverty head count, population, network density and distance to big cities, all in natural logarithm. In the case of OLS with clustered errors: robust standard errors in brackets below the coefficient are clustered by markets. $\hat{p} < 0.10$, $\hat{p} \leq 0.05$, $\hat{p} \leq 0.01$.

Table 4b Impact of mobile phones on prices and margins: full sample, PSM/KM

dependent variable	ln(margin), seasonally adjusted ln(p _{m,sa} /p _{f,sa})	ln(producer price), seasonally adjusted ln(p _{f,sa})	ln(retail market price), seasonally adjusted ln(p _{m,sa})
ATT	0.045*** (0.015)	-0.100*** (0.027)	-0.055** (0.027)
ATU	0.077	0.022	0.098
ATE	0.055	-0.061	-0.005
treated, on support	317	317	317
treated, off support	1643	1643	1643
untreated, on support	151	151	151
untreated, off support	797	797	797
no. of observations	2908	2908	2908

Note: see note above. $\hat{p} < 0.10$, $\hat{p} \leq 0.05$, $\hat{p} \leq 0.01$. To construct seasonally adjusted prices, we first regress ln(p) on market, month-year and market-specific seasonality, next, use this estimation to construct a predicted price ln(p_{seas}) and finally, calculate the natural log of the seasonally adjusted prices as ln(p)-ln(p_{seas}). Common support and standardized bias of covariates is reported in the appendix.

Table 4c Impact of mobile phones on prices and margins: full sample, IV/2SLS

dependent variable	ln(margin) ln(p _m /p _f)	ln(producer price) ln(p _f)	ln(retail market price) ln(p _m)
mobile phone	0.060*** (0.014)	-0.157*** (0.023)	-0.097*** (0.021)
centered R ²	0.4991	0.8471	0.8511
uncentered R ²	0.8239	0.9995	0.9996
Sargan statistic	317.0 (0.000)	353.3 (0.000)	470.9 (0.000)
no. of observations	2913	2913	2913

Note: Sargan statistic is an over-identification test of all instruments (p-value in brackets). Instruments are population, poverty head count and network density, all in natural logarithm, apart from trend, market and year-month fixed effects and market specific seasonality.

Sensitivity analyses and robustness checks

Next, we explore if the results of the estimated base specification can (approximately) be maintained under several variations of specification and sample. We consider an alternative way of deflating prices, a sample period that starts at the first year of access to mobile phones and ends when full access is realised, a geographical split-up of the sample, and a split-up by market on the basis of the average size of the margin.

In our basic specification prices are deflated with the country-wide uniform consumer price index. However, prices of consumer goods vary, both over time and between markets¹⁶. To make prices comparable over time and between markets, we need to deflate the maize producer and market prices with a price index that takes account of both these variations¹⁷. Unfortunately we only have a standard and uniform Mozambique consumer price index (CPI) that does not take account of different developments of consumer goods prices between markets. Hence, deflating prices with the national CPI introduces measurement error in the estimations¹⁸. Alternatively, we can exploit the property that the national consumer price index (CPI) is nearly fully explained by a trend: under the assumption that the national CPI is a weighted sum of CPIs of markets, where the CPI of each market is determined by a (market-specific) trend and an intercept, we re-run estimations with nominal prices as dependent variable and include a full set of market specific trends as explanatory variables, as an approximation for the diverging development in local consumer prices. Likewise we can construct seasonally adjusted price series on the basis of nominal prices and re-run PSM

¹⁶ During the period of study (from July 1997 to December 2009) consumer prices increased on average around 10% annually. Hence, an assumption that consumer prices are (approximately) the same in this period cannot be maintained: over time prices of consumer goods increase substantially. Moreover, markets are also located very far apart: the largest road distance between markets is more than 2000km. This makes diverging price developments across markets likely.

¹⁷ Note that by construction deflation is not necessary for the margin series.

¹⁸ This makes the estimations of the price margin slightly more trustable as this problem is, by construction, absent.

estimations. This strategy takes account of developments that are likely to be different between markets and thereby seems more flexible in this dimension¹⁹.

From the data description section we know that already in 2006 access to mobile phone technology is realised in the 15 markets identified in this study. As a result observations with and without access to mobile phone technology are approximately balanced in 2005-2006. Hence, there is no need in the estimations to move the sample far beyond 2006. Potential confounding factors will play a larger role if the sample is extended far beyond the date of introduction, and this may adversely affect the accuracy of impact estimates. Also, mobile phone technology in our sample of markets is introduced in the year 2000. Including observations of years prior to 1999 may, for similar reasons, deteriorate accuracy of impact estimates. Hence, we have re-run the basic specification with a sample period adjusted accordingly.

Mozambique is a large country²⁰. Differences in impact are possibly associated with differences in behaviour and circumstances in different parts of the country. A natural way to make a geographical split-up of markets is by considering markets north and south of the Zambezi river. Markets on either side of the Zambezi are likely to operate independently, to a certain degree, due to high transport costs of trade across the Zambezi river (see Zant, 2017b). As a matter of fact: major flows of maize grain are, north of the Zambezi, from west to east, and, south of the Zambezi, from central to south: producer areas in the north (like Mocuba and Cuamba) supply cities and towns on the coastline, north of the Zambezi, while producer areas in the central region (like Manica and Chimoio) mainly supply deficit regions

¹⁹ Approximating local consumer price indices with a trend of course ignores (differences of) within-season variation of consumer prices. Especially in agricultural based economies this is likely to be an issue.

²⁰ Road distance from north to south (Pemba-Maputo) is 2500-2800km (for comparison: New York – Houston (Texas): 2650km; Amsterdam-Gibraltar: 2400-2600km).

in the south and Maputo (see also Zant, 2017b)²¹. Hence, as a robustness check we are keen to investigate similarities or differences in patterns on both sides of the Zambezi.

For reasons that are not fully clear, markets have very different average margins (see descriptive section). We assume that these differences are associated with differences between markets in transaction costs and trader activity. Costs to purchase and collect maize grain from farmers in the neighbourhood will vary between markets. In some cases farmers are located in isolated, far away and widely dispersed areas, while in other cases farmers are close-by and concentrated in a small area. Alternatively, markets may differ by the number of traders and the competition among traders: in some markets many traders are active, competing with each other for profitable purchases from farmers. This will lead to higher farm gate prices and lower margins. Conversely, margins will increase with little trader activity and low levels of competition between traders. A change in information and a related change in search costs may affect markets with different levels of transaction costs and competition differently and this explains the final robustness check: we split the sample in high and low margin markets and investigate if impacts differ between these two types of markets.

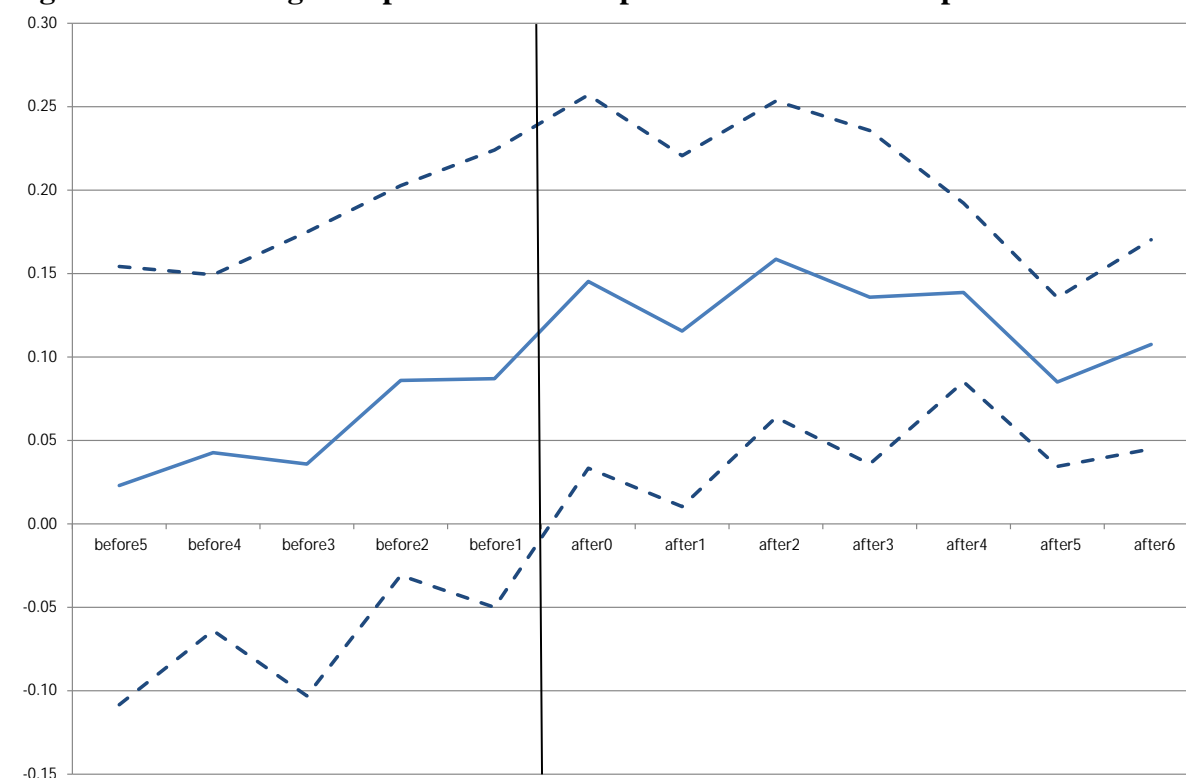
The sensitivity analyses and robustness checks – of which estimation results are reported in the appendix – generate different outcomes, but overall consistently confirm the estimation of the basic specification in the main text. In the estimations for south of Zambezi the introduction of mobile phones causes price levels to increase rather than decrease, which , contrasts with results for the full sample and north of Zambezi. The bias in benefit towards traders, however, remains.

²¹ It should be noted, however, that the current paper does not address spatial arbitrage (see Zant, 2017a for an analysis of the impact of mobile phones on spatial arbitrage).

6. Other potential threats and alternative explanations

For the Dif-in-Dif estimations to be convincing it is required that margins and prices are all on a parallel trend before the introduction of mobile phones. It is most popular to show graphically that this parallel trend assumption is satisfied. In order to construct the required information we estimate equation (1) slightly adjusted: the impact variable is substituted for a set of annual indicator variables reflecting the number of years before and after the introduction of mobile phones. Hence, if $d(\text{year}0)$ is an indicator variable with a value of 1 in the year of introduction and zero elsewhere, then $d(\text{year}-1)$ [$d(\text{year}+1)$] is an indicator variable with a value of 1 one year before (after) introduction and zero elsewhere, etc. If the pre introduction trends between with and without mobile phones are the same, then the pre introduction coefficients should be insignificant: the difference in differences is not significantly different between the two groups in the pre-treatment period (see Autor, 2003, for an application of this test).

Figure 5 Testing for a parallel trend: impact of access to mobile phones



Note: dotted lines indicate 95% confidence intervals

The figure clearly indicates that all *before* coefficients are statistically insignificant and thereby support a common trend in the observations before the introduction of mobile phones. The figure further consistently supports similarly sized and statistically significant impacts after the introduction of mobile phones. This makes us confident about the robustness of estimation results reported in Table 1.

7. Follow-up: verification, other impacts, outside options and explanation of results

How to proceed this research? An obvious strategy is to analyse other types of data, like household and trader surveys, after matching these with the rollout data. With survey data on farm households we can investigate if measured impacts obtained with price data are consistent with those extracted from household surveys. From the previous work it is clear that the timing of transactions is key to assess survey based unit values. The richer survey data could also reveal what price information is available to and used by farmers, and farmers' involvement in trading activities. With information on the production and marketing side, households surveys may further be helpful in exploring other behavioural responses to the introduction of mobile phones (for example crop choice, market participation and storage). Finally, survey data may shed light on the character of the bargaining process with traders (number of villages traders, frequency of price offers, multiple traders or repeat transactions with the same trader, collusion between traders, contractual arrangements, outside options) (Mitra et al., 2018).

Hence, in the first place we want to know how farm gate selling prices, extracted from these surveys, respond to access to mobile phones and verify the time series data results obtained in this study. Secondly, actual use of mobile phones and other ICT services could be verified as well. Further, in the third place, we may explore how access to mobile phones affects input use, crop composition, market participation (in maize, but also in all crops), and storage behaviour. Also heterogeneity across farmers may be important. Do wealthy farmers

have a different response vis-à-vis poor farmers? Do farmers living near to markets have a different response vis-à-vis farmers living remote from markets? Do quantities sold / available for sale influence the response? (see Fafchamps and Vargas Hill, 2005).

Another alternative for investigation is to identify how the information base or outside options for farmers and traders is affected by the introduction of mobile phones. This may, for example be implemented by estimating which (lagged) prices (for example market prices in the home market, nearby market or the nearest large city market) in particular drive the impact of mobile phones. Changes in the outside option for farmers and traders as a result of the introduction of mobile phones could further reveal the characteristics of the underlying bargaining process.

The key topic to elaborate is the explanation of the (lack of) impacts found in the empirical sections of this study. More specifically, how come that farmers are not able to benefit from mobile phones? How come that mobile phones are not helpful in decreasing asymmetric information and in increasing competition between traders? What are the constraints that farmers face to exploit mobile phones?

8. Summary and conclusion

In this study we investigate if the introduction of mobile phones in Mozambique has brought an income gain to farmers or traders. We investigate this by analysing producer and retail market prices, and the margin between maize producer and retail market prices. The evidence indicates an increase in the margin that varies from 4.5% to 9.6%. Hence, we find benefits from mobile phones that accrue to traders, rather than to farmers. To answer the question raised in the title: the evidence does not support less asymmetric information and increased trader competition, but rather the reverse. Impacts on producer and market prices

independently vary but confirm the margin results. Estimation results are robust for non-random rollout of the mobile phone network and several other threats.

With these results there are two major (and related) questions that pop up. First, how do these results compare with the literature and, secondly, why are farmers not able to benefit from improved information. Various other authors also find a weakly or not significant impact of the introduction of mobile phones on received prices, farmers' welfare and behaviour (Muto and Yamano, 2009; Fafchamps and Minten, 2012; Tadesse and Bahiigwa, 2015; Aker and Ksoll, 2016). Others, however, do find a positive impact (Jensen, 2007; Svensson and Yanagizawa, 2009; Goyal, 2010). It is not exactly clear how to reconcile these different results: the easy answer is that circumstances are most likely different in these different studies. But what than exactly is different? Or what exactly cause farmers in one study to benefit and in another study not to benefit? Several alternatives are suggested to further investigate these questions.

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Appendix

Nominal prices, using markets specific trends to deflate:

Table A1a Impact of mobile phones on prices and margins: full sample, OLS/DiD

dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.084*** (0.014)	0.087*** (0.015)	-0.121*** (0.024)	-0.073*** (0.025)	-0.037* (0.022)	0.014 (0.023)
covariates	no	yes	no	yes	no	yes
clustering of errors	no	no	no	no	no	no
adj R ²	0.5170	0.5176	0.9315	0.9322	0.9377	0.9386
no. of observations	2899	2899	2899	2899	2899	2899
dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.084* (0.047)	0.087* (0.049)	-0.121* (0.067)	-0.073 (0.071)	-0.037 (0.086)	0.014 (0.082)
covariates	no	yes	no	yes	no	yes
clustering of errors	yes	yes	yes	Yes	yes	yes
R ²	0.5676	0.5687	0.9387	0.9393	0.9443	0.9451
no. of observations	2899	2899	2899	2899	2899	2899

Note: Maize price data are from July 1997 to December 2009 (source: SIMA). All estimations include market and year-month fixed effects, and control for market specific seasonality and trends. The latter (approximately) control for variations in consumer price, both over time and between markets. Covariates are poverty head count, population, network density and distance to big cities. In the case of OLS with clustered errors: robust standard errors in brackets below the coefficient are clustered by markets. $p < 0.10$, $p \leq 0.05$, $p \leq 0.01$.

Table A1b Impact of mobile phones on prices and margins: full sample, PSM/KM

dependent variable	ln(margin), seasonally adjusted ln(p _{m,sa} /p _{f,sa})	ln(producer price), seasonally adjusted ln(p _{f,sa})	ln(retail market price), seasonally adjusted ln(p _{m,sa})
ATT	0.036** (0.015)	-0.095*** (0.028)	-0.059** (0.027)
ATU	0.057	0.043	0.100
ATE	0.042	-0.051	-0.009
treated, on support	317	317	317
treated, off support	1645	1645	1645
untreated, on support	147	147	147
untreated, off support	797	797	797
no. of observations	2906	2906	2906

Note: see note above. $p < 0.10$, $p \leq 0.05$, $p \leq 0.01$. For the construction of seasonally adjusted prices, we first regress ln(p) on market, month-year and market-specific seasonal dummies and trends, next, use this estimation to construct a predicted price ln(p_{seas}) and finally, calculate the natural log of the seasonally adjusted prices as ln(p)-ln(p_{seas}). See appendix for common support graphs and standardized bias of covariates.

Table A1c Impact of mobile phones on prices and margins: full sample, IV/2SLS

dependent variable	ln(margin) ln(p _m /p _f)	ln(producer price) ln(p _f)	ln(retail market price) ln(p _m)
mobile phone	-0.017 (0.024)	-0.202*** (0.039)	-0.219*** (0.035)
centered R ²	0.5391	0.9353	0.9411
uncentered R ²	0.8380	0.995	0.9996
Sargan statistic	52.9 (0.000)	144.7 (0.0000)	200.9 (0.0000)
no. of observations	2913	2913	2913

Note: Sargan statistic is an over-identification test of all instruments (p-value in brackets). Instruments are trend, population, poverty head count and network density, all in natural logarithm, and apart from market and year-month fixed effects and market specific seasonality.

Table A2a Impact of mobile phones on prices and margins: 1997-2005, OLS/DiD

dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.056*** (0.015)	0.101*** (0.017)	-0.070*** (0.023)	-0.011 (0.027)	-0.014 (0.021)	0.089*** (0.024)
covariates	no	yes	no	yes	no	yes
clustering of errors	no	no	no	no	no	no
adj R ²	0.4650	0.4774	0.7963	0.7997	0.8113	0.8238
no. of observations	1860	1860	1860	1860	1860	1860
dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
cell phone dummy	0.056 (0.052)	0.101* (0.047)	-0.070 (0.040)	-0.011 (0.050)	-0.014 (0.069)	0.089*** (0.058)
covariates	no	yes	no	yes	no	yes
clustering of errors	yes	yes	yes	yes	yes	yes
R ²	0.5315	0.5431	0.8216	0.8249	0.8347	0.8460
no. of observations	1860	1860	1860	1860	1860	1860

Note: Maize price data are from July 1997 to December 2009 (source: SIMA). All estimations include market and year-month fixed effects, and control for market specific seasonality. Prices are deflated with the national consumer price index. Covariates are poverty head count, population, network density and distance to big cities. In the case of OLS with clustered errors: robust standard errors in brackets below the coefficient are clustered by markets. $\hat{p} < 0.10$, $\hat{p} \leq 0.05$, $\hat{p} \leq 0.01$.

Table A2b Impact of mobile phones on prices and margins: 1997-2005, PSM/KM

dependent variable	ln(margin), seasonally adjusted ln(p _{m,sa} /p _{f,sa})	ln(producer price), seasonally adjusted ln(p _{f,sa})	ln(retail market price), seasonally adjusted ln(p _{m,sa})
ATT	0.064*** (0.017)	-0.095*** (0.031)	-0.031 (0.031)
ATU	0.088	0.015	0.102
ATE	0.071	-0.060	0.012
treated, on support	304	304	304
treated, off support	614	614	614
untreated, on support	142	142	142
untreated, off support	806	806	806
no. of observations	1866	1866	1866

Note: see note above. $\hat{p} < 0.10$, $\hat{p} \leq 0.05$, $\hat{p} \leq 0.01$. For the construction of seasonally adjusted prices, we first regress ln(p) on market, month-year and market-specific seasonal dummies and trends, next, use this estimation to construct a predicted price ln(p_{seas}) and finally, calculate the natural log of the seasonally adjusted prices as ln(p)-ln(p_{seas}). See appendix for common support graphs and standardized bias of covariates.

Table A2c Impact of mobile phones on prices and margins: 1997-2007, IV/2SLS

dependent variable	ln(margin) ln(p _m /p _f)	ln(producer price) ln(p _f)	ln(retail market price) ln(p _m)
mobile phone	0.027 (0.016)	-0.151*** (0.026)	-0.124*** (0.023)
centered R ²	0.4904	0.8052	0.8146
uncentered R ²	0.8217	0.995	0.9996
Sargan statistic	253.7 (0.0000)	332.7 (0.0000)	429.4 (0.0000)
no. of observations	2327	2327	2327

Note: Sargan statistic is an over-identification test of all instruments (p-value in brackets). Instruments are trend, population, poverty head count and network density, all in natural logarithm, and apart from market and year-month fixed effects and market specific seasonality.

Table A3a Impact of mobile phones on prices and margins: north, OLS/DiD

dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.041** (0.018)	0.062*** (0.019)	-0.113*** (0.033)	-0.077** (0.035)	-0.073** (0.031)	-0.015 (0.033)
covariates	no	yes	no	yes	no	yes
clustering of errors	no	no	no	no	no	no
adj R ²	0.6535	0.6642	0.9512	0.9546	0.9538	0.9560
no. of observations	1295	1295	1295	1295	1295	1295
dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.041 (0.031)	0.062* (0.031)	-0.113 (0.088)	-0.077 (0.057)	-0.073 (0.074)	-0.015 (0.035)
covariates	no	yes	no	yes	no	yes
clustering of errors	yes	yes	yes	yes	yes	yes
R ²	0.7162	0.7257	0.9600	0.9629	0.9621	0.9641
no. of observations	1295	1295	1295	1295	1295	1295

Note: Maize price data are from July 1997 to December 2009 (source: SIMA). All estimations include market and year-month fixed effects, and control for market specific seasonality. Prices are deflated with the national consumer price index. Covariates are poverty head count, population, network density and distance to big cities. In the case of OLS with clustered errors: robust standard errors in brackets below the coefficient are clustered by markets. $p < 0.10$, $p < 0.05$, $p < 0.01$.

Table A3b Impact of mobile phones on prices and margins: north, PSM/KM

dependent variable	ln(margin), seasonally adjusted ln(p _{m,sa} /p _{f,sa})	ln(producer price), seasonally adjusted ln(p _{f,sa})	ln(retail market price), seasonally adjusted ln(p _{m,sa})
ATT	0.043** (0.020)	-0.115*** (0.033)	-0.072** (0.031)
ATU	0.091	0.022	0.112
ATE	0.071	-0.036	0.035
treated, on support	131	131	131
treated, off support	298	298	298
untreated, on support	180	180	180
untreated, off support	406	406	406
no. of observations	1015	1015	1015

Note: see note above. North excludes Angonia. $p < 0.10$, $p < 0.05$, $p < 0.01$. For the construction of seasonally adjusted prices, we first regress ln(p) on market, month-year and market-specific seasonal dummies and trends, next, use this estimation to construct a predicted price ln(p_{seas}) and finally, calculate the natural log of the seasonally adjusted prices as ln(p)-ln(p_{seas}). See appendix for common support graphs and standardized bias of covariates.

Table A3c Impact of mobile phones on prices and margins: north, IV/2SLS

dependent variable	ln(margin) ln(p _m /p _f)	ln(producer price) ln(p _f)	ln(retail market price) ln(p _m)
mobile phone	0.110** (0.047)	-0.183** (0.074)	-0.073 (0.063)
centered R ²	0.5731	0.8774	0.9017
uncentered R ²	0.8384	0.9996	0.9997
Sargan statistic	32.871 (0.0000)	13.093 (0.00144)	3.607 (0.16472)
no. of observations	1369	1369	1369

Note: Sargan statistic is an over-identification test of all instruments (p-value in brackets). Instruments are trend, population, poverty head count and network density, all in natural logarithm, and apart from market and year-month fixed effects and market specific seasonality.

Table A4a Impact of mobile phones on prices and margins: south, OLS/DiD

dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.074 (0.080)	-0.018 (0.092)	0.124 (0.118)	0.261* (0.138)	0.198** (0.098)	0.242** (0.114)
covariates	no	yes	no	yes	no	yes
clustering of errors	no	no	no	no	no	no
adj R ²	0.5960	0.6099	0.9539	0.9542	0.9629	0.9636
no. of observations	1430	1430	1430	1430	1430	1430
dependent variable	ln(margin) ln(p _m /p _f)		ln(producer price) ln(p _f)		ln(retail market price) ln(p _m)	
mobile phone	0.074* (0.033)	-0.018 (0.031)	0.124*** (0.030)	0.261*** (0.044)	0.198*** (0.063)	0.242*** (0.070)
covariates	no	yes	no	yes	no	yes
clustering of errors	yes	yes	yes	yes	yes	yes
R ²	0.6492	0.6620	0.9600	0.9603	0.9678	0.9685
no. of observations	1430	1430	1430	1430	1430	1430

Note: Maize price data are from July 1997 to December 2009 (source: SIMA). All estimations include market and year-month fixed effects, and control for market specific seasonality. Prices are deflated with the national consumer price index. Covariates are poverty head count, population, network density and distance to big cities. In the case of OLS with clustered errors: robust standard errors in brackets below the coefficient are clustered by markets. $p < 0.10$, $p \leq 0.05$, $p \leq 0.01$.

Table A4b Impact of mobile phones on prices and margins: south, PSM/KM

dependent variable	ln(margin), seasonally adjusted ln(p _{m,sa} /p _{f,sa})	ln(producer price), seasonally adjusted ln(p _{f,sa})	ln(retail market price), seasonally adjusted ln(p _{m,sa})
ATT	0.054** (0.026)	0.057** (0.025)	0.111*** (0.027)
ATU	0.063	0.003	0.067
ATE	0.056	0.046	0.102
treated, on support	283	283	283
treated, off support	1002	1002	1002
untreated, on support	75	75	75
untreated, off support	136	136	136
no. of observations	1496	1496	1496

Note: see note above. $p < 0.10$, $p \leq 0.05$, $p \leq 0.01$. For the construction of seasonally adjusted prices, we first regress ln(p) on market, month-year and market-specific seasonal dummies and trends, next, use this estimation to construct a predicted price ln(p_{seas}) and finally, calculate the natural log of the seasonally adjusted prices as ln(p)-ln(p_{seas}). See appendix for common support graphs and standardized bias of covariates.

Table A4c Impact of mobile phones on prices and margins: south, IV/2SLS

dependent variable	ln(margin) ln(p _m /p _f)	ln(producer price) ln(p _f)	ln(retail market price) ln(p _m)
mobile phone	-0.010 (0.042)	0.132** (0.062)	0.123** (0.053)
centered R ²	0.5924	0.8908	0.8983
uncentered R ²	0.8665	0.9997	0.9998
Sargan statistic	116.664 (0.0000)	151.564 (0.0000)	197.881 (0.0000)
no. of observations	1544	1544	1544

Note: Sargan statistic is an over-identification test of all instruments (p-value in brackets). Instruments are trend, population, poverty head count and network density, all in natural logarithm, and apart from market and year-month fixed effects and market specific seasonality.

**Table A5 First stage logistic estimation of propensity score:
probability of access to mobile phone technology**

Dependent variable: probability of access to mobile phone technology (cell, binary)			
Sample	full sample	north of Zambezi	south of Zambezi
estimation technique	Logit	Logit	Logit
Variables			
Trend	0.879*** (0.066)		
ln(poverty head count)	-21.43*** (1.805)	-33.51*** (2.725)	-33.44*** (2.837)
ln(population)	0.915*** (0.123)	0.735*** (0.180)	
ln(network density)	3.659*** (0.497)		
ln(distance to city)		-3.562*** (0.440)	-6.520*** (0.722)
pseudo R2	0.8304	0.7285	0.6597
Observations	2908	1015	1496

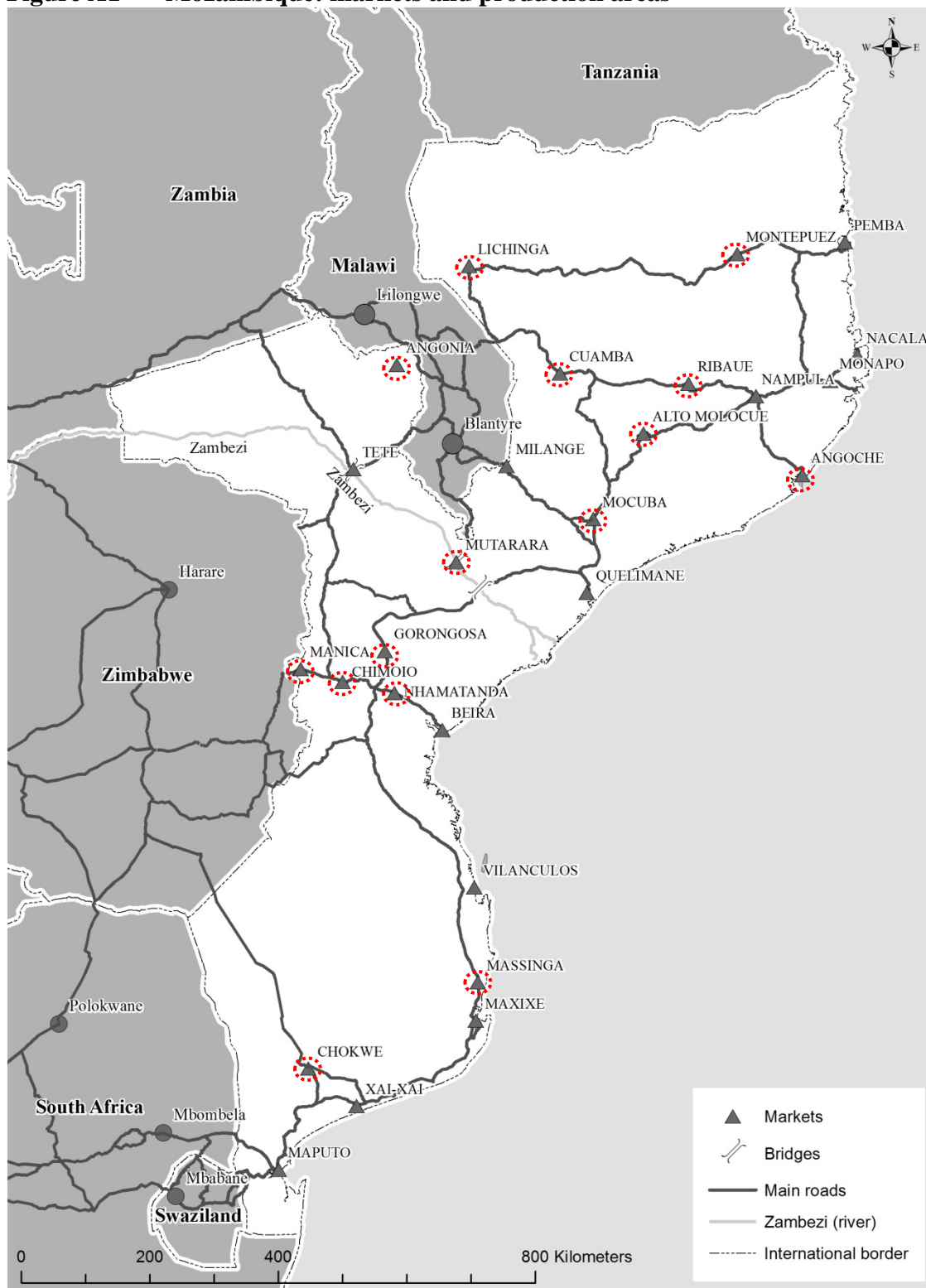
Standard errors are in brackets next to the coefficient. $p < 0.10$, $p < 0.05$, $p < 0.01$. The statistics in the table correspond with the Propensity Score Matching estimates with Kernel Matching reported in the main text and the appendix.

Table A6 Standardized Bias of Covariates, before and after Matching

Sample	full sample		north of Zambezi		south of Zambezi	
	before	after	before	after	before	After
Trend	1109.9	49.8				
ln(poverty head count)	-133.5	-854420	0.958	2.693	-93.6	-1027370
ln(population)	500.5	115.6	-7790.8	-60151.4		
ln(network density)	264.3	81.6			-76.8	-68.7
ln(distance to city)			-1764.9	-679.3		

Note: $B = \frac{(\bar{X}_T - \bar{X}_C)}{(\sqrt{(\bar{X}_T - \bar{X}_C)^2 / N})}$ where \bar{X}_T , \bar{X}_C and $\sqrt{(\bar{X}_T - \bar{X}_C)^2 / N}$ are, respectively, the average and variance of covariate X in the treatment (control) group (Rosenbaum and Rubin, 1985). The standardized bias, B, is calculated before and after matching, for each covariate X. The statistics in the table are all scaled for presentational purposes and correspond with the Propensity Score Matching estimates with Kernel Matching reported in the main text and the appendix.

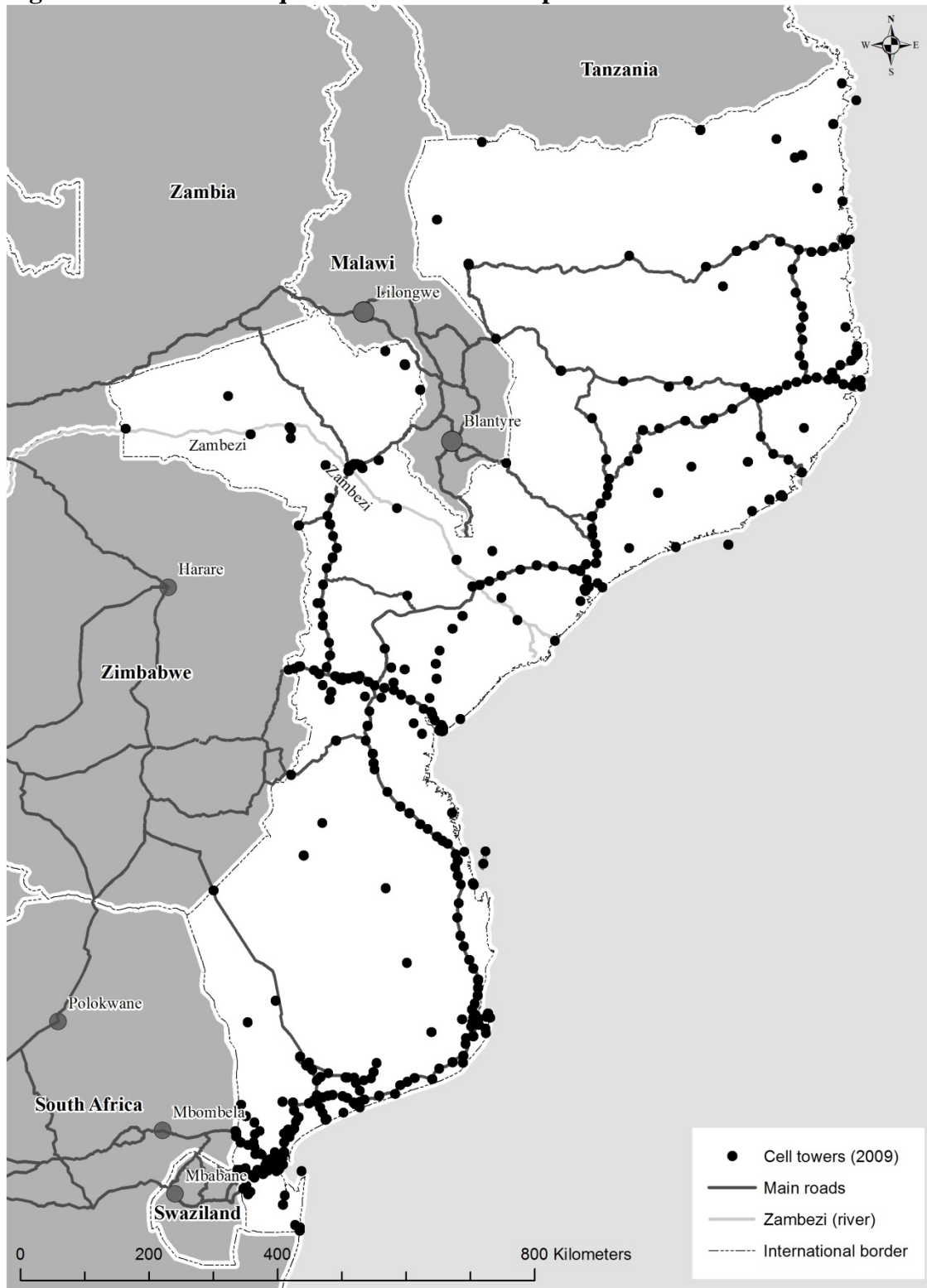
Figure A1 Mozambique: markets and production areas



Source: VU SPINlab

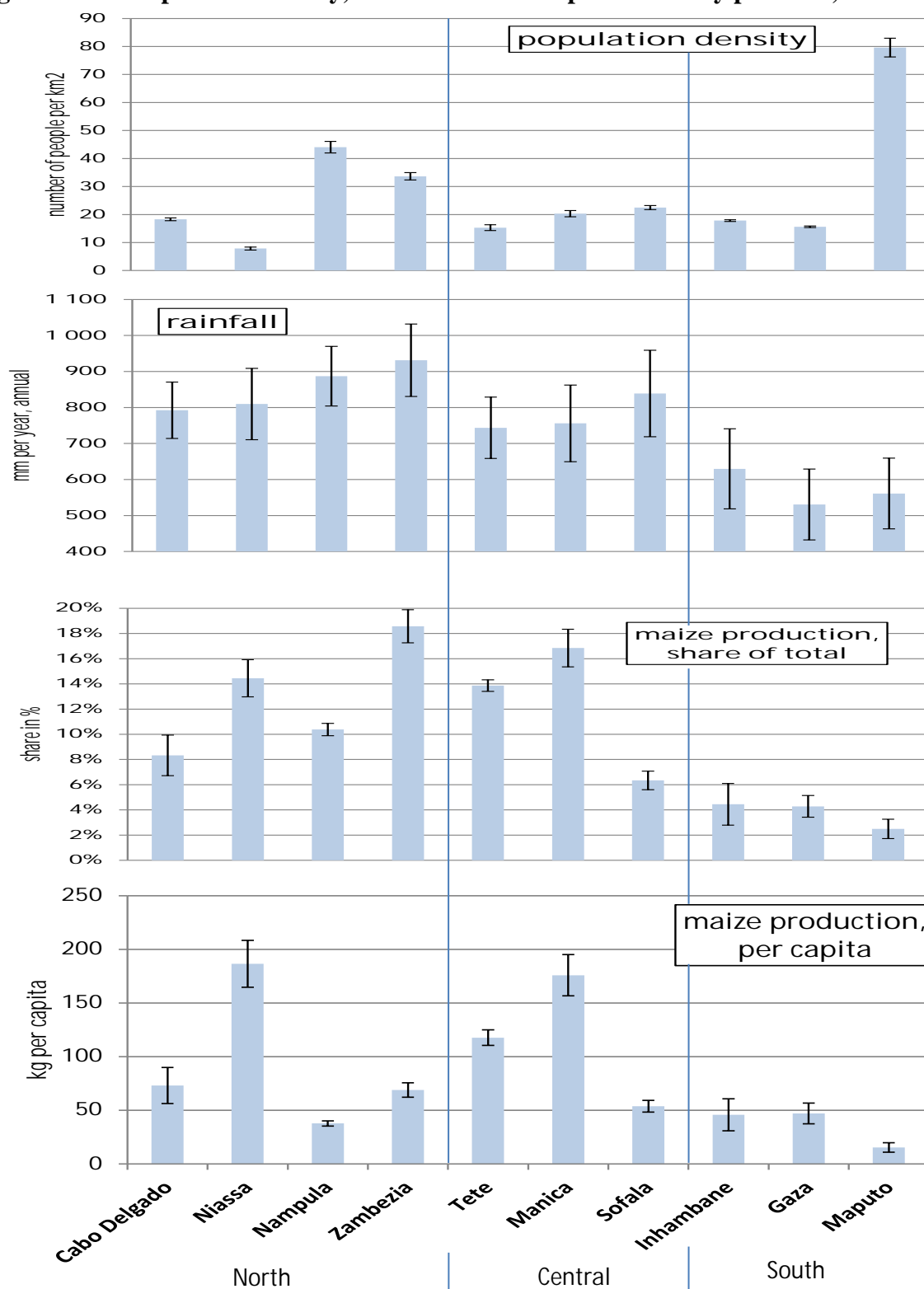
Note: Producer markets for which SIMA producer prices are available are circled.

Figure A2 **Mozambique: network of mobile phone towers in 2009**



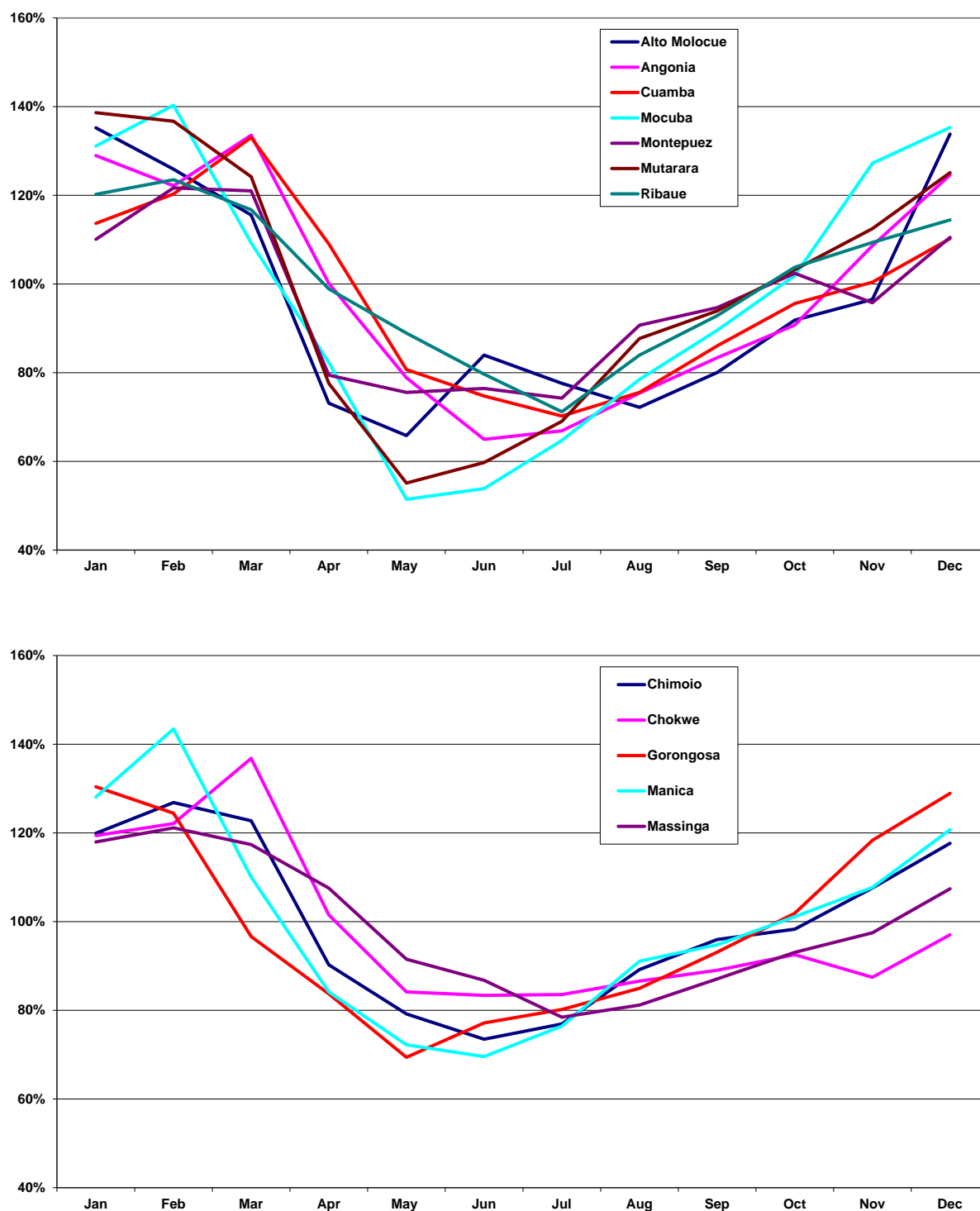
Source: VU SPINlab

Figure A3 Population density, rainfall and maize production by province, 1999-2007



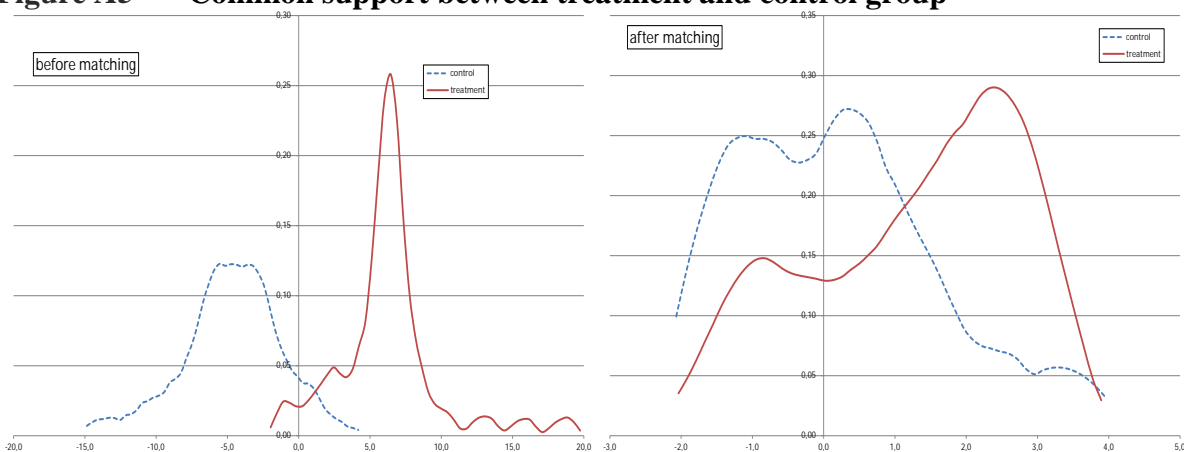
Source: (author's calculations based on data from) Instituto Nacional de Estatística Moçambique, FEWSNET and Ministry of Agriculture, Early Warning Unit (Aviso Previo); The figure is based on aggregate (average) annual province data. Error bars show 95% confidence intervals. See the maps in this appendix for the location of provinces.

Figure A4 Seasonality of Market Maize Prices by Market

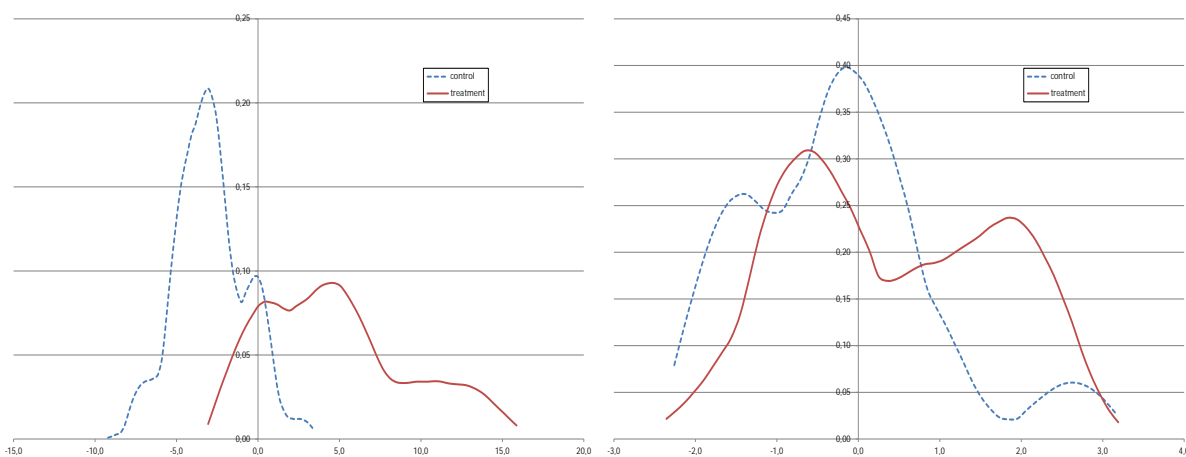


Note: The figures plot average monthly prices by market as a percentage of (centered) average annual prices in these markets, averaged over the years (1997-2009). It should be noted that averaging over the years disguises substantially larger seasonality that results from droughts.

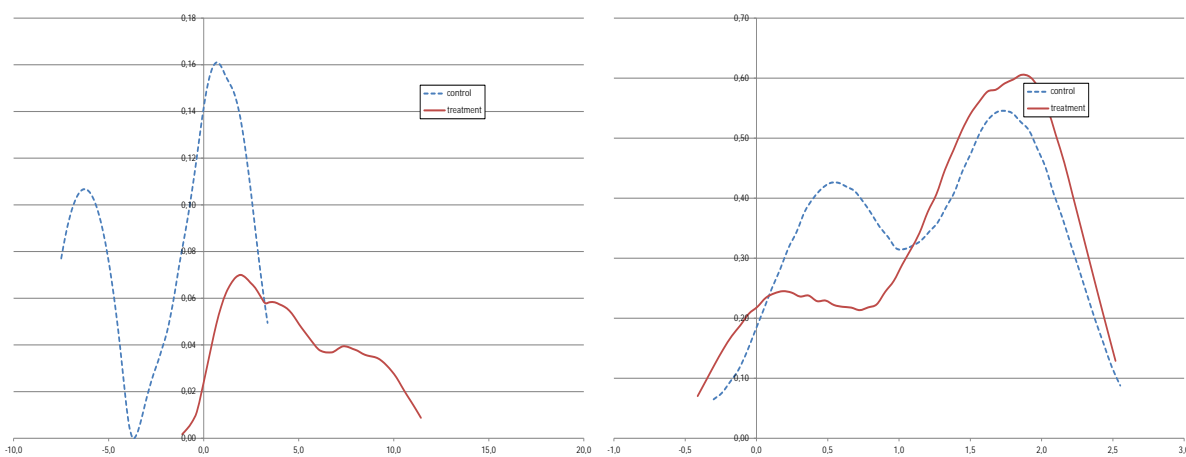
Figure A5 Common support between treatment and control group



Note: PSM, Kernel Matching, full sample (July 1997-December 2009, all markets; Table 3b)



Note: PSM, Kernel Matching, north of Zambezi (July 1997-December 2009; Table 4b)



Note: PSM, Kernel Matching, south of Zambezi (July 1997-December 2009; Table 5b)