Final report

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Market Linkages, Trade Costs, and Technology Adoption in Rural Tanzania: Preliminary Evidence from a Pilot in Kilimanjaro Region*

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Abstract

Poor transportation infrastructure is believed to limit adoption of productivity enhancing technologies like chemical fertilizer, but there is little research which quantifies the effects of remoteness on market access, especially for agricultural inputs. We provide novel evidence on market access for smallholder farmers using self-collected data on the supply chain for chemical fertilizer and for maize in each of the 570 villages in the Kilimanjaro region of Northern Tanzania. Our data includes (1) surveys with farmers in 110 randomly selected villages; (2) surveys with all agro-retailers, or "agrovets," in the region; (3) the collection of information on road quality, travel times, and travel costs; (4) driving times and distances pulled from Google Maps API; and (5) interviews with maize-buying agents and distributors. Our reduced form results show that doubling transport costs to the primary regional market is associated with a \$1.7 increase (8%) in the delivered price for chemical fertilizer, and a reduction in adoption of this technology by 14 percentage points (25%). We further quantify these effects using a spatial model of agro-retailers, and evaluate the impact of supply chain shocks on adoption.

JEL Codes: F14, O12, O13, O18, Q12

Keywords: market access, inputs, technology adoption, transport costs, roads

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1 Introduction

It is widely believed that poor access to markets – due mainly to poor transportation infrastructure – limits agricultural productivity in rural areas of developing countries, by making it harder to access productivity-enhancing inputs like fertilizer and to obtain high prices for crop output (World Bank, 2008; 2017).[1] However, while remoteness no doubt limits market access, there is little research to rigorously quantify its effect, especially in the case of input adoption.

In this paper, we rigorously document market access among farmers in the Kilimanjaro region of Northern Tanzania. Our data collection exercise spans the entire supply chain in all 570 villages in the Kilimanjaro region, including (1) surveys with a sample of 550 farmers in 110 randomly selected villages; (2) surveys with all 369 agro-retailers, or "agrovets," in the region; (3) the collection of information on road quality, travel times, and travel costs to all villages from markets as well as major urban centers; (4) driving times and distances pulled from Google Maps API for the universe of bilateral village pairs, as well as for pairs of villages and major urban centers in the region; and (5) interviews with maize-buying agents and distributors. This region includes a great deal of heterogeneity in remoteness – varying from villages just a few kilometers from the major town where fertilizer is distributed to villages located in remote mountains 200 km away – and so provides enough variation to examine fairly substantial changes in travel costs.

The first part of our paper is a reduced form investigation of the correlation between different measures of market access and remoteness. We find clear evidence of reduced market access in remote areas, along virtually every measure that we study. Because we have geocoordinates for the entire universe of villages and agrovets in the region, we calculate the minimum travel cost-adjusted price for fertilizer that is available as our primary measure of price dispersion. Travel costs are substantial: as a percentage of the best retail price available, farmers pay the equivalent of a 12.1 percent iceberg cost, or 10.8 percent of total expenditures.[2] We find that a doubling of remoteness increases this price by about 10 percent,. We also find that farmers in remote areas have fewer retailers to choose from, and consistent with this, farmers in remote areas are substantially less likely to use fertilizer: doubling transport costs is associated with a 14 percentage point reduction in fertilizer use (on a base of 55 percent), with even larger effects on quantities. On the output side, remote farmers are much less likely to sell maize, have lower harvest output, and are more likely to be net buyers of maize.

To quantify the impact of transport costs and other factors on input adoption, we develop a spatial model of the market for fertilizer. In the model, the decision to adopt fertilizer is based on local output prices, idiosyncratic farmer productivity, the distribution of input prices, and

[1] Transportation infrastructure is particularly underdeveloped in Africa as the continent has only 137 kilometers of roads per 1000 square kilometers of land area, with only a quarter paved. In contrast, the average for developing countries outside the region is 211 kilometers of roads per 1000 square kilometers, with more than half paved (World Bank, 2010). For comparison, the US has 679 kilometers per 1000 square kilometers, with nearly 2/3 paved.

[2] This is a lower bound since there may be other costs of distance that we do not consider, such as information frictions, or that risk averse, credit constrained farmers may be wary to incur large travel costs to travel to distant and likely unknown retailers that may stockout or sell them inputs of poor quality.

idiosyncratic shocks. Transportation costs affect the distribution of prices by increasing the cost for the farmer to reach a particular agrovet. To account for the fact that we may not fully capture the bundle of inputs that a farmer purchases at a given location (or other heterogeneity in pricing power by an agrovet), we allow for an unobserved agrovet-specific scalar on the delivered cost of fertilizer. Functionally, this yields a first-order condition for each agrovet that is a function of transport-adjusted demand, and its firm-specific ability to maintain a high price.

We aggregate demand in standard multinomial logit form, and essentially execute a Berry (1994) inversion in "reverse" to recover agrovet-specific effects that rationalize mark-ups (which we measure). Given the structure of the model, we can perfectly match agrovet pricing, and then use the model to conduct three counterfactuals. In the first, we halve transportation costs for farmers to reach all villages. In response to this shock, mark-ups change very little since the the spatial distribution of transport costs has not changed all that much. However, overall adoption increases by 6 percentage points, or approximately 10 percent over the baseline mean. In districts with low baseline adoption of fertilizer, the percentage effect is even larger. For a second counterfactual, we examine the effects of a 50 percent increase in output prices, where this shock is meant to measure a downstream shock to demand (such as a large influx of output buying intermediaries or access to a foreign market with higher prices). The effect of such an output price shock is positive in most areas, though more modest in relative terms when compared to the transport shock. Finally, we evaluate the impact of a 50 percent reduction in the wholesale price for fertilizer, which puts the Kilimanjaro average price roughly on-par with the world price (thereby eliminating all mark-ups). This shock has a relatively large impact on adoption, increasing adoption from the baseline mean by 10 percentage points, or 16 percent. Retailer mark-ups double with this shock, implying that retailers capture some of the cost shock as profits.

This paper sits at the intersection of trade and development economics, and we hope to provide value to both literatures. Our primary question considers the impact of remoteness on the price, availability, and adoption of fertilizer by rural farmers. Sub-Saharan Africa has lagged far behind the rest of the developing world in agricultural technology adoption (World Bank 2007) despite evidence that improved technologies could generate large *yield* increases (i.e. Duflo, Kremer and Robinson 2008; Beaman et al. 2013; Stewart et al. 2005; Udry and Anagol 2006). The *profitability* of these technologies thus depends on the relative prices of fertilizer and crop output, and on the size of the yield increase. The literature is more divided on whether these technologies are profitable, with some papers finding large returns (i.e. Duflo, Kremer and Robinson 2008) and others lower or even negative returns (i.e. Beaman et al. 2013). While this previous literature has mostly focused on measuring yield increases, profitability is equally affected by relative prices, the focus of this paper. Our results quantify the extent to which profitability, and thus adoption, will tend to be lower in more remote locations.

Our paper is also differentiated from much of the development literature by focusing on market access, rather than on demand side explanations like farmer knowledge and learning spillovers (Foster and Rosenzweig, 1995; Conley and Udry 2010; Bandiera and Rasul, 2006; Emerick, 2017), credit, liquidity or insurance constraints (Bardhan and Mookherjee, 2011; Maitra et al., 2017; Karlan et al., 2015), or behavioral explanations (Duflo, Kremer and Robinson. 2011; Hanna, Mullainathan, and Schwartzstein, 2014).[3] Our work is most closely related to Suri (2011), who shows that many Kenyan farmers with high gross returns to hybrid seeds choose not to adopt them because the fixed costs of obtaining seeds are too high, presumably due to travel costs. Our paper is differentiated by focusing on heterogeneity in market access, rather than on heterogeneity in returns.

Our paper is related to a rapidly growing literature about the effect of roads or other infrastructure improvements on development outcomes and on the spatial distribution of economic activity.[4] Many of these papers evaluate large-scale infrastructure programs as natural experiments, or by employing structural techniques, and thus provide causal evidence on the effect of *roads* on various outcomes. The key difference in our paper is that we focus narrowly on the specific effect of transportation costs on market access (i.e. the actual time and money costs of transportation and the presence of intermediaries and the prices they charge) in isolation, without changing other margins.[5] Building roads may change many outcomes other than just prices, including consumption diversity (Aggarwal, 2017), human capital investment (Adukia et al., 2016, Aggarwal 2017), migration (Morten and Oliveira 2016), occupation choice (Asher and Novosad 2016), as well as many others such as electrification, proximity to health care, etc.[6] By contrast, our goal is to focus solely on the effect of remoteness on intermediary entry and pricing, with special emphasis on chemical fertilizer.[7]

Our work is related to a voluminous trade literature. Within this literature, price differentials across space can be attributed to three primary components – marginal trade costs (eg. Donaldson, forthcoming; Eaton and Kortum, 2002; Keller and Shiue, 2007; Sotelo, 2016), spatially varying mark-ups (Atkin and Donaldson, 2015; Asturias et al., 2017), and the organization of intermediaries (Allen and Atkin, 2016; Dhingra and Tenreyro, 2017; Bergquist, 2017; Casaburi and Reed, 2017). Simply quantifying these price differences is important for the literature, as there is a dearth of data studying rural markets, and in particular, access to inputs. We collected price and sales information by firm, input-type and brand - essentially "scanner" data - including wholesale prices for these items, which facilitates an exact measure of retail mark-ups. Further, our unique transportation

[3]See Foster and Rosenzweig (2010) and Jack (2013) for reviews of this literature.

[4]A partial listing of papers includes Aggarwal (2017), Alder (2017), Adukia et al. (2016), Asher and Novosad (2016), Banerjee et al. (2012), Bird and Straub (2016), Bryan and Morten (2017), Gertler et al. (2014), Ghani et al. (2016), Khanna (2016), Shamdasani (2016), and Storeygard (2016). See Donaldson (2016) for a review.

[5]Technological advances may make it possible to decouple market access from traditional road infrastructure. For example, Rwanda has a "droneport" already under construction just outside the city of Kibuye, where drones capable of transporting cargo of up to 20 kilos over a distance of 100 kms already exist.

[6]Indeed, several papers in this literature just use overall economic development (as proxied by night lights) in order to, among other reasons, capture the all-pervasive nature of the impacts generated by road construction. See, for example, Alder (2017), Khanna (2016), and Storeygard (2016).

[7]In the specific context of agricultural inputs, both Aggarwal (2017) and Shamdasani (2016) find evidence of increased input adoption in the wake of a pan-Indian rural road construction program. However, the impact documented by both of these papers is reduced form in nature and neither is able to establish either the impact of transport costs on decreasing adoption or the channels through which road construction encourages adoption.

surveys allow us to calculate the exact cost of acquiring inputs for all possible locations in our sample.

Our paper is closely related to Atkin and Donaldson (2015), who estimate trade costs in a situation in which an oligopolist intermediary buys products at wholesale prices, transports them to distant markets and sells them directly to consumers. By contrast, we are interested in how trade costs affect the buying decisions of final consumers (in this case, farmers), as well as pricing decisions by retailers (though this is not fully explored in this draft). Though not directly comparable since they are at different points in the supply chain, our average ad-valorem "trade costs" of farmers procuring fertilizer turn out to be similar to those of the intermediaries in Atkin and Donaldson (2015). Our costs, however, are calculated over a much shorter trip.[8] Using our quantitative model, shocking these transport costs to "US" levels has a moderate impact on adoption, especially in districts with low baseline adoption rates. On the output side of the market, we collect novel descriptive measures of intermediary behavior, in particular, the entry of output buying "agents." Allen and Atkin (2016) models a similar channel, where a perfectly competitive, heterogeneous group of traders travel from market to market exploiting all available arbitrage opportunities.[9] Different from the the data used in their work, we measure intermediation directly at the level of the farmer - whether crops are sold, and if so, in what quantity and at what price. Indeed we have found an active supply network for maize that is run by intermediaries, we find that many farmers are not served by them, and that distance to the nearest market and nearest town significantly reduces the probability of being served. We also motivate future work using the quantitative model, showing that a plausible shock to output conditions has a moderate effect on fertilizer adoption, especially in markets with low baseline adoption rates.

Finally, much of the trade literature, which has documented larger gains from integration when there are input-output relationships (eg. Yi, 2001; Costinot and Rodriguez-Clare, 2014; Sotelo, 2016) has only evaluated economies under the assumption of monopolistically competitive or purely competitive sectors at a fairly aggregate level (eg. international trade by industry).[10] By contrast, our model is based on a standard discrete-choice logit model in which farmers choose the best agrovet from which to purchase fertilizer. In contrast to the previous literature, such a model allows for reductions in transport costs to be absorbed in part by increased mark-ups by the retailer. Largely, we find that the mark-up channel has an discernable effect on adoption only when the source of the shock is to wholesale prices.[11]

[8] Specifically, to find the best travel-adjusted price for fertilizer, our results suggest that for the typical village, the best option is 10km away. In Atkin and Donaldson, ad-valorem estimates are calculated based on the cost difference of a trip to the most remote location (500 miles away) relative to the least remote location (50 miles away), which is approximately a 720km difference.

[9] In Allen and Atkin (2016), when a particular market has excess supply, less efficient intermediaries enter that "route" to exploit the new arbitrage opportunity. In their work, they use this model to quantify the role of revenue volatility in crop choice, and use a highway project in India to evaluate how crop choice affects the gains from integration.

[10] Our work is closely related to Sotelo (2016) develops a model of regional trade in agriculture and road quality in Peru to study the impact of road and output shocks on regional welfare and crop choice. Our work differs in its focus on local intermediaries and how their presence affects the landscape of market access.

[11] Yi (2001) provides an influential take on the role of vertical relationships in the growth of vertical trade that is

The rest of this paper proceeds as follows. Section 2 provides background and context on our study region, and lays out the sampling strategy that was adopted for this project. Section 3 explains the data, and documents summary statistics about the various data-collection units. Section 4 presents our main results. We put our findings in the context of a spatial model, which is presented and calibrated in Section 5, and run policy counterfactuals. Section 6 concludes with a discussion.

2 Background and Sampling Strategy

2.1 Background on fertilizer market and Kilimanjaro region

This study took place in the Kilimanjaro region[12] of Northern Tanzania. There are 570 villages in the region, and according to the 2012 census of Tanzania, the total population of the area is 1.6 million, about three-quarters of which is rural (National Bureau of Statistics, 2013). Our data collection covers the entire area of the region, a substantial area of 13,250 square-kilometers, roughly equivalent to the state of Connecticut in the USA or the country of Montenegro. Within Tanzania, Kilimanjaro is a relatively prosperous region, and agricultural productivity is relatively high. Using data provided by the 2012-13 wave of the National Panel Survey, we find that farmers in Kilimanjaro reported maize yields that are about 30 percent higher than the national average. Roads within Kilimanjaro are also marginally better than in Tanzania on the whole - according to numbers reported by the government of Tanzania, the paved trunk road density in Kilimanjaro is 2.2 percent of the total land area in the region (i.e., there are 2.2 kilometers of roads per 100 square kilometers of area), as opposed to only 0.7 percent for Tanzania as a whole. The density of the total network of trunk and regional roads is 7.4 percent in Kilimanjaro, but only half as much (3.7 percent) for the entire country of Tanzania (TanRoads and PMO-RALG, 2014).[13] The relative density of other minor roads is likely similar, although these numbers are harder to obtain. From an objective standpoint however, the road network in Kilimanjaro is quite poor. For instance, the density of the road network in the United States is 68 percent; the OECD average is 134 percent.[14]

Kilimanjaro has two growing seasons: a longer, more productive "long rains" season, which runs from March to June, and a less productive "short rains" season from October to January. Input usage tends to be much higher in the long rains, and some farmers decide not to plant in the short rains at all. Our main outcomes are based on behavior in the long rains.

germane to our work. Intuitively, if inputs are traded from one country to another, and then final goods are traded back to the origin country, the role of distance is amplified by the multiple stages of production. That is, since borders must be crossed more than once, the costs of distance are amplified by the number of times the good crosses the border prior to consumption. Our field work has identified that economy in rural Tanzania is similar to this setting, where inputs are sourced from larger cities, and output, if sold at all, is trade back to these same cities.

[12] Tanzania has 31 regions in all, including 5 in Zanzibar.

[13] The Roads Act, 2007 (No. 13 of 2007) defines a a trunk road as one that is primarily (i) a national route that links two or more regional headquarters or (ii) an international through route that links regional headquarters and another major or important city or town or major port outside Tanzania. A regional road is a secondary national road that connects (i) a trunk and district or regional headquarters; (ii) a regional headquarters and district headquarters.

[14] Information compiled from various online resources.

We worked off of the list of villages included in the documents pertaining to the 2012 census of Tanzania, and did data-collection in the universe of villages (570 villages) listed as being in the Kilimanjaro region. As discussed in more detail below, we conducted surveys in a subset of villages, and did a comprehensive census of agro-input retailers in the entire region.

Virtually all fertilizer is imported in Tanzania. While some developing countries (such as India) produce chemical fertilizer domestically, production capacity is virtually non-existent in sub-Saharan Africa, and therefore, many sub-Saharan African nations import the entirety of their fertilizer requirements (FAOSTAT Online database, 2016; Hernandez and Torero, 2011).[15] As a result, for these countries, transport costs from port to farm will directly affect prices. At present, we do not document the costs from port to distributor, but collect costs from that point on. In particular, we focus on the rural costs of intermediation and the costs at which farmers acquire inputs from retailers. To our knowledge, documenting the latter costs is entirely novel within the literature.

2.2 Sampling Strategy

The goal of this project is to construct a dataset representative of the entire region of Kilimanjaro. The main categories of data we set out to measure were: (1) surveys of farmers, fertilizer retailers, and maize buyers; (2) transportation costs; and (3) prices. We initially set out to measure prices of a variety of goods. However, many villagers do not purchase most of their goods in their local village, and instead travel to local markets which operate one or several days a week. We decided to use these markets as the unit at which we would measure prices.

Thus, to construct our sample, we first assigned every village in our sample to a market catchment area. This was done by visiting ward offices (the ward is the lowest administrative level in Tanzania) and asking the ward officer to list the market that people from that village frequented. We use this market information in two main ways. First, we randomly selected markets for inclusion in the price collection from this list. Second, it was not feasible to travel individually from every village to a particular point to measure transport costs. Instead, we measure transport costs, requiring routes to go through the market center – we measure distances from every village to its closest market, and from every market to the main road. A map of the villages in our sample is included as Figure 1.

The geography of Kilimanjaro region provides for a setting with potential wide variation in transportation costs to Moshi. Closest to Moshi are semi-urban and rural districts surround the city. While many villages may be located off main roads, their location is proximate to the main supply points in the region. In the northeastern part of Kilimanjaro, near the border with Kenya, many villages are by straight-line distance not far from Moshi, but the the presence of Mt. Kilimanjaro is complicating for travel. Further removed from Moshi are villages near the town of Same, itself connected to Moshi by the main trunk road within the region. However, even along this road,

[15] Tanzania has some limited domestic production capacity in the form of an Arusha-based company called Minjingu Mines and Fertilizer Ltd. Only a handful of retailers in our sample sell this brand of fertilizer, however.

travel times are not trivial, and many villages are located within, or on the other side of, the Pare Mountains (to the northeast of Same). Overall, the region provides substantial geographic variation that we now document in terms of the costs of travel.

3 Data and summary statistics

We have three main sources of data we use in this draft. All were collected from January 2016 to April 2017.

3.1 Agrovet surveys

First, we conducted a census of all agrovets in the region, finding a total of 395 agrovets. Of these agrovets, 376 sell fertilizer, which will be our primary sample. We then revisited these agrovets to conduct a longer survey which took about 2 hours to complete. The survey asked questions about varieties of fertilizer sold, prices, quantities, and the wholesale costs of acquiring stock from the distributor. The survey took care to differentiate fertilizer types by distributor, brand, and type – thus the level of granularity should be akin to the barcode-level. The survey also included a number of questions about costs of travel to the distributor, as well as some background characteristics.

3.2 Farmer surveys

We conducted farmer surveys in a randomly sampled subset of 115 villages.Within a selected village, enumerators were instructed to first find the "center" of the village.[16] Once the village center was identified, the enumerators randomly picked a direction to begin their fieldwork, and selected every third homestead, or the next homestead after five minutes of walking, whichever came first. Overall, we enrolled an average of 4.8 farmers in 118 villages. The survey itself included questions on input usage and prices, maize sales, harvest output, and related outcomes. The survey also included some household and demographic questions.

3.3 Measuring transport costs

We measured transportation costs in several ways. First, we collected GPS location for every village in Kilimanjaro,[17] from which we calculated driving times and distances using the Google API (via the statistical program R). Second, we conducted surveys of transportation operators in every village in our sample, which were either motorbike taxis ("Boda Bodas"), or consumer van taxis ("Dala Dalas"). In each village, we asked up to 3 operators how much it cost to travel to the

[16] Of course, the center isn't always easy to know, so enumerators were instructed to consider the following options as origin points: a primary/secondary school within the village (1st choice), local church within the village (2nd), Boda stand within the village (3rd).

[17] We cross-checked these GPS coordinates, and filled in a handful of missing values, using a dataset of postal geocodes from www.geopostcodes.com).

major towns in Kilimanjaro (Arusha and Moshi), the capital city (Dar es Salaam) and the market center.

Third, enumerators recorded information on road quality and travel times as part of their field work. There are several major paved roads in Kilimanjaro. While not up to developed country standards, these roads are better maintained and most are paved. They are typically 2 lane roads. To get to a village, it is typically necessary to turn off one of these main roads and then travel for some time on unpaved feeder roads and village roads. To measure travel times, field officers used the following protocol. On a GPS unit, they recorded the point at which they had to turn off the main road, and then recorded the travel time, distance, and road quality on the road to the market center associated with the village. Once reaching the market, enumerators took a second form of transportation to the village, recording again distance, travel time, and road quality. We use this data to correlate costs of travel with road quality, and to estimate the percentage of roads which are paved (to inform later counterfactuals).

3.4 Agent surveys, store surveys and logbooks

To measure market access on the output side, we collected several surveys. Farmers who sell maize will either do so locally (typically to a vendor who then sells to other consumers or, more rarely, the farmer may retail it directly) or to an intermediary known as a "maize agent." Agents visit villages just after harvest and offer to buy maize in bulk. Agents then organize transportation of the maize to other locations. The bulk of this maize is transported to the major local towns in the region (Arusha and Moshi) to be sold to large maize warehouses known as "stores." The largest stores have capacity for tens of thousands of bags of maize. Store owners sell maize in bulk to major buyers in other locations (as well as to local vendors and to consumers). For example, much of the maize in Kilimanjaro is transported north to Nairobi, Kenya.

Interviewing agents and stores is challenging, because there is no registry of these types of businesses and because agents are itinerant, moving from village to village. To construct a sample of agents and to get information on maize flows, we asked a selected subset of the largest maize stores to keep a logbook. Each store was given a bound book in which they were asked to record each major transaction, recording the price, quantity and the method of transportation. In order to collect information about agents, stores were asked to record the name and phone number of each agent that they purchased maize from, as well as the location from where they came. We also surveyed stores, asking questions about maize volumes, prices, and transportation costs, as well as some background and demographic questions.

Using the list of agents and their contact information from the store logbooks, we called agents to schedule appointments for a survey. This survey included questions similar to the stores, but also asked questions about where agents traveled to buy maize, what price they paid in different locations, methods of transportation, and storage of purchased maize.

While we intend to use this data in future iterations of this paper, we do not use results from these surveys in the current draft.

3.5 Price collection

This project was initially centered around collecting prices in rural markets, but then evolved towards rigorously documenting market access for farmers, and centering the project around the surveys listed above. However, we did collect price information for a period of time. We enrolled 45 markets into a price-collection protocol, conducted from March-August 2016. To enroll participants, we visited each market and selected several types of retailers for project inclusion, including fertilizer retailers ("agrovets"), maize sellers, and retail shops. Each respondent was called once per month and asked about current retail and wholesale prices for each item in a pre-selected list of standardized goods (e.g., 200 ml box of Azam juice). Respondents were compensated for participation by mobile money transfer. We do not utilize the price data in this current draft but intend to do so in future iterations.

3.6 Summary statistics

Summary statistics are provided in Table 1 for villages (Panel A), roads (Panel B), and farmers (Panel C). The average village has 2,842 people, and is located 5.7 kilometers from the nearest market center. A round-trip to the market center takes about 40 minutes according to surveys (20 minutes according to Google maps), and costs about US $1.60. The average distance to the nearest major town of Moshi is about 65 km, and a round-trip there would take just under 3 hours and cost about $4.70. These travel costs are substantial for poor farmers making a few dollars a day.

There is also substantial variation in travel costs to these cities in the region, from towns just outside Moshi to remote villages in the mountains in Same District in the South of Kilimanjaro. The standard deviation of travel costs to Moshi is about 80% of the mean, while the minimum travel cost is about $0.30 and the maximum is $22. Figure 2 shows a CDF of village travel costs, indicating substantial heterogeneity within the region. In this context, it is reasonable to consider counterfactuals of even very large increases in travel costs.

Panel B shows information on the quality of the rural roads connecting markets and villages. Roads are about 1/3 paved, 1/3 dirt, and 1/3 gravel, and travel times according to google are fairly slow: 30.6 km/hour on rural roads compared to 49.5 km/hr on the main roads.[18]

Panel C shows summary statistics on farmers. Fifty-five percent of farmers use fertilizer, substantially higher than the national average reported in the Tanzania NPS. Conditional on using, farmers tend to use about 50 kilograms (close to the FAO recommendation for 1 acre of land – so much less than FAO recommendations given that the average farmer has 2.7 acres of land). It is very rare for farmers to use smaller quantities, however (which is consistent with fixed transport costs discouraging small amounts of fertilizer use). Most farmers (83%) use improved seeds of some sort. A minority of farmers (38%) sell maize, and about half of these sales are to agents (the rest are local sales). Conditional on selling, farmers sell large quantities (850 kg). Finally, agricultural productivity appears very low – the average farmer harvested only 800 kg on a 2.7 acre farm, worth

[18] However, note from panel A that travel times on google, at least on rural roads, are about half the travel times experienced by enumerators.

only about \$180 at average post-harvest prices. These yields are too low to survive on alone, so most farmers have other sources of income.

4 Main results

4.1 Specification

From the above data sources, we are able to construct transportation costs to every village in our sample, using either survey transport costs or Google maps. Our main empirical specification then becomes:

$$m_{fvt} = \beta_0 + \theta d_{vt} + \epsilon_{fvt} \tag{1}$$

where m_{vt} is a measure of market access and d_{vt} is the (log) cost of travel from the village to the nearest city where fertilizer is distributed (Moshi). In future drafts we will incorporate other controls into these regressions including, where available, farmer characteristics and soil information from the FAO-GAEZ; in the current version, these are just bivariate regressions. We run these regressions at the village level in Table 2, and on the farmer data in a representative sample of villages in Table 3 (clustering standard errors by the village).

In Table 4, we run regressions among agrovets (again clustering by village). We view these regressions as more descriptive than the previous tables, since the decision of an agrovet to enter a market is endogenous and thus we only observe outcomes in locations in which a retailer chose to enter. However, one advantage of using the agrovet data is that we have information on essentially barcode-level fertilizer brands, allowing us to run a regression at the agrovet-brand level, clustering standard errors by agrovet.

While most of our outcomes are intuitive, our primary measure of access to fertilizer requires some explanation. Farmers are free to travel to any agrovet from which they want to purchase, so long as they can afford the transportation cost. Thus, if travel costs are low enough, then a farmer who has a high-cost local alternative will simply travel to a farther market – suggesting that the price at her local agrovet is not particularly informative of her market access. To calculate effective price dispersion, we impute the cost of travel from each village to every agrovet in the region (from our surveys and Google), and calculate travel-cost adjusted prices for a 50 kg bag of fertilizer. We assume that a farmer must make 3 one-way trips to purchase the bag (a round-trip for herself plus one additional trip for the fertilizer itself – this is based on qualitative field reports), and we impute a cost of travel of 175 Tsh per km (about \$0.076).

4.2 Market Access

In Table 2 and subsequent tables, we present the mean and standard deviation of the dependent variable in Column 1, and regression results in Columns 2-4. Panel A shows variable constructed solely from information at the village level (transport surveys and geocodes, primarily). The average minimum travel cost-adjusted price is \$21.9, with a standard deviation of \$3.1, indicating meaningful variation in access to inputs across villages. Columns 2-4 show strong evidence that travel cost-adjusted prices are higher in more remote villages. A doubling of distance from Moshi raises travel cost-adjusted prices by $1.70, or about 8%. To obtain this price, a farmer in the average village must travel about 10 km and must pay about $2.36 in travel costs. This is approximately 12.1% ad-valorem equivalent. In reality, the average farmer who buys fertilizer travels only 5 km from her village (see Figure 3), which we posit may be because the time costs of travel are high, or because there are other costs of distance (such as less information about distant retailers, or concerns about the risk of a stockout). We hope to explore this in future work but for now do not have the data to explore these channels. In any case, the predicted distance a farmer must travel is significantly higher in remote areas. We also see clear evidence that rural areas have fewer retailers and are less likely to have retailers within a radius of 5 or 10 km.

4.3 Farmers

Table 3 shows farmer results. Panel A shows that a doubling of transport costs is associated with a 14 percentage point decline in fertilizer adoption (against a base of 55%), and an even larger decline in quantities of nearly 50%. Remoteness is also negatively correlated with improved seed usage. In part due to these results, we find significantly lower yields in rural areas – a doubling of transport costs reduces harvest output by nearly 25%. Farmers are much less likely to interact with agents or sell to agents, and are more likely to buy maize.

Of course, the causality of some of these outcomes is unclear – the prices of all imported goods are higher in rural areas, and remoteness may have other negative effects. Panel B looks at some other measures from the survey. We find differences between villages along these measures here, but they are less extreme than for the farming outcomes – the farmers we surveyed were younger and less likely to have bank or mobile money accounts and were less likely to have a market business. Their farms are larger, however. Other measures like home quality, years of education, and cell phone ownership do not significantly differ.

In future work, we plan to refine these results by including more controls, notably soil characteristics from the FAO-GAEZ and other characteristics from the census and from the farmer survey.

4.4 Agrovets

Our final set of reduced form results is from the agrovets. We view these regressions as more descriptive than definitive, since they include an inherent selection bias (we can only observe an agrovet if that agrovet had chosen to enter). Nevertheless, we view these results as important supportive evidence. Figure 4 shows histograms of retail prices, wholesale prices, and markups, showing quite a bit of variation in retail prices and markups but less on the wholesale price (note that markups do not currently include transportation costs but will be adjusted in future drafts). The lack of variation in wholesale prices is because most agrovets pick up fertilizer from the wholesaler and transport it back themselves. Interestingly, we find little effect of distance on the types or quantities of fertilizer sold. However, consistent with the previous results, we find that remote retailers charge higher prices (again a doubling of transport costs is associated with around a 10% increase in the price). We plan to investigate these results further in future work. Model and calibration

To quantify the impact of transportation costs on farmers, using the data collected from farmers and agrovets, we evaluate counterfactuals related to farmer transportation costs, output prices and input prices on agrovet pricing and adoption decisions. To begin, we outline a model of fertilizer adoption and agrovet pricing.

4.5 Farmers and Fertilizer Adoption

Suppose that there are I farmers, indexed by i, that own land K_i and may purchase fertilizer to improve the productivity. Later on, we will define the unit of observation as the village, which will be averaged across surveyed farmers within the village, but for exposition it is easier to focus on the farmer for now.

Farmers maximize wealth, and they use this wealth to fund other (unmodeled) consumption. Below, we evaluate a model in which farmers choose whether or not to buy fertilizer to increase yields on some portion of their land, and if so, where they should be purchasing their fertilizer to improve productivity.

When a farmer in location i uses a bag of fertilizer, wealth rises by $p_i\alpha_i$, where α_i is the yield increase of using fertilizer for farmer i and the value of this increase is proportional to the output price. This yield increase, and variation in the yield increase that is specific to each farmer, is meant to capture unobserved variation that may be due to soil quality, farmer ability, or other factors that are unobserved at the farmer level.

For farmers who buy fertilizer, suppose that they choose to buy fertilizer from agrovet j at a price r_j. To travel to and from agrovet j, the farmer must pay F_{ij}. Recognizing that there may be other economic reasons that a farmer may go to location j (other items available, near other stores, higher reliability), we assume that farmers face an agrovet-specific cost sensitivity, δ_j, to the delivered costs of fertilizer, $F_{ij} + r_j$. We also assume an idiosyncratic error ε_{ij} for location j by farmer i that is independent of other factors. Thus, for a farmer that chooses location j, wealth is written as:

$$W_{ij} = p_i K_i + p_i \alpha_i - (F_{ij} + r_j)\,\delta_j + \varepsilon_{ij} \tag{2}$$

The usefulness of having δ_j in the model will become apparent shortly. Essentially, it will act as a "residual" in the first order condition that allows us to perfectly match mark-ups, conditional on adoption decisions and imputed market shares.[19]

[19] Typically in an empirical IO model, brand quality would be an additive term that is eventually backed-out of the data by contraction. If δ_j were additive, it would not effect the demand elasticity other than through the implicit effect on market shares. We have tested the model under that assumption and we cannot match observed mark-ups to the data. Thus, we use a multiplicative approach, which is similar to the location-specific scale in Cosar, Grieco,

For those farmers who do not adopt, their wealth is a simple function of their endowment and idiosyncratic error. Precisely:

$$W_{i0} = p_i K_i + \varepsilon_{i0} \tag{3}$$

To characterize the discrete choice model in terms of probabilities, we assume that all idiosyncratic εs are distributed Gumbel; thus, the model yields the standard multinomial logit choice probabilities. Recognizing that only differences in wealth matter within multinomial logit, it follows directly that the probability farmer i chooses agrovet j is written as:

$$\lambda_{ij} = \frac{\exp\left(p_i\alpha_i - \left(F_{ij} + r_j\right)\delta_j\right)}{1 + \sum_s \exp\left(p_i\alpha_i - \left(F_{is} + r_s\right)\delta_s\right)} \tag{4}$$

A useful transformation of this for the empirical analysis is:

$$\lambda_{ij} = \frac{\exp\left(-\left(F_{ij} + r_j\right)\delta_j\right)}{\sum_s \exp\left(-\left(F_{is} + r_s\right)\delta_s\right)}\mu_i \tag{5}$$

where μ_i is the probability that farmer i adopts fertilizer, and is defined as:

$$\mu_i = \frac{\sum_s \exp\left(p_i\alpha_i - \left(F_{is} + r_s\right)\delta_s\right)}{1 + \sum_s \exp\left(p_i\alpha_i - \left(F_{is} + r_s\right)\delta_s\right)} \tag{6}$$

With the farmer's problem described, we now move to the pricing optimization for agrovets.

4.6 Agrovet Pricing

Keeping with the i index from above, we now assume that a farmer i is representative of the village, which has L_i similar farmers. Any characteristics for each village i will be averaged across surveyed farmers from that village.

For an arbitrary agrovet j, profits are written as follows,

$$\Pi_j = \left(r_j - r_j^o\right)\sum_i L_i\lambda_{ij} \tag{7}$$

where r_j^o is the price at which agrovet j purchases fertilizer from a distributor. The simplicity of logit is apparent when deriving the effects of r_j on λ_{ij}.

$$\frac{d\lambda_{ij}}{dr_j} = -\delta_j\lambda_{ij}\left(1 - \lambda_{ij}\right) \tag{8}$$

Li and Tintelnot (2017).

Thus the first order conditions for agrovet j can be written as:

$$\frac{\partial \Pi_j}{\partial r_j} = \sum_i L_i \lambda_{ij} - \left(r_j - r_j^o\right) \sum_i L_i \delta_j \lambda_{ij} \left(1 - \lambda_{ij}\right) = 0 \tag{9}$$

Rearranging, we can solve for the absolute mark-up, $r_j - r_j^o$:

$$r_j - r_j^o = \frac{\sum_i L_i \lambda_{ij}}{\delta_j \sum_i L_i \lambda_{ij} (1 - \lambda_{ij})} \tag{10}$$

In 10, we see that level mark-ups are a function of village sizes, the probability each village buys from j, and the agrovet-specific cost sensitivity δ_j.

4.7 Calibration

In the model, we have J agrovet pricing equations and I adoption probabilities. We seek to solve for J δ_j's and I α_i's using these equations.

Since multinomial logit does not allow for zero probabilities for any option, we first need to smooth out the ones and zeros we have for adoption data to probabilities of adoption. For simplicity, we simply assign a 0.01 for surveyed villages without adoption, and 0.99 for surveyed villages with full adoption. These adoption probabilities will be shown as "baseline" in later figures. In future drafts, we will integrate an estimation of these probabilities simultaneously within the pricing equations.

With these adoption probabilities, we can proceed to backing out unobserved parameters in the model. First, we begin with δ_j's. Rearranging (10), and imposing the second definition of selecting agrovet j (from 11), we get:

$$\delta_j = \left(\frac{1}{r_j - r_j^o}\right) \frac{\sum_i L_i \frac{\exp(-(F_{ij}+r_j)\delta_j)}{\sum_s \exp(-(F_{is}+r_s)\delta_s)} \mu_i}{\sum_i L_i \frac{\exp(-(F_{ij}+r_j)\delta_j)}{\sum_s \exp(-(F_{is}+r_s)\delta_s)} \mu_i \left(1 - \frac{\exp(-(F_{ij}+r_j)\delta_j)}{\sum_s \exp(-(F_{is}+r_s)\delta_s)} \mu_i\right)} \tag{11}$$

There are J of these equations, and we solve these equations for all δ_j's using a non-linear solver in R. As long as the data are scaled appropriately (so that we're not trying to calculate exp(50000000)), the system converges to a solution very quickly.

Next, using the μ_i's and the δ_j's, we can directly solve for the unobserved α_i's, which again are interpreted as farmer-specific yield increases from using a bag of fertilizer. To see how, note that the probability of fertilizer adoption is written as:

$$\mu_i = \frac{\exp\left(p_i \alpha_i\right) \sum_s \exp\left(-\left(F_{is} + r_s\right) \delta_s\right)}{1 + \exp\left(p_i \alpha_i\right) \sum_s \exp\left(-\left(F_{is} + r_s\right) \delta_s\right)} \tag{12}$$

Rearranging, we have:

$$p_i \alpha_i = \log\left(\frac{\mu_i}{1 - \mu_i} \frac{1}{\sum_s \exp\left(-\left(F_{is} + r_s\right) \delta_s\right)}\right) \tag{13}$$

Note that it is possible for $p_i\alpha_i$ to be negative, i.e. that using fertilizer actually decreases yields. This is solely an artifact of the particular model that we are using. Essentially, given the values of δ_j and observed fertilizer prices and transport costs, any remaining variation in adoption is absorbed by the term $\exp(p_i\alpha_i)$. These terms are always positive, but may be less than one. Intuitively, for any villages low adoption but also relatively low delivered prices for fertilizer, the lack of adoption will be attributed to the village component and $\exp(p_i\alpha_i)$ will be relatively small. Since maize prices are always positive, then only way that $\exp(p_i\alpha_i)$ can be small is for α_i to be negative.[20]

4.8 Counterfactuals

With all α_i's and δ_j's in hand, we now use the model to evaluate the effects of cost shocks on agrovet prices, mark-ups and adoption probabilities. As motivated in the introduction, the decision to adopt fertilizer can be affected by both sides of the supply chain, as well as by the degree of access to markets that sell inputs. To this end, we evaluate three counterfactuals

1. Decrease wholesale fertilizer prices by 50%
2. Increasing all maize (output) prices by 50%
3. Decreasing transport costs by 50%

These counterfactuals are designed to bring the Kilimanjaro region "in-line" with developed country standards. For example, the world price of Urea fertilizer during July-September of 2014 was approximately \$310/metric ton. In Moshi Urban during this same period, the price was approximately \$640/metric ton. Thus, the first counterfactual is meant to capture "giving the world price" to agrovets, thereby eliminating all trade costs and mark-ups from the port. The second counterfactual is meant to capture the larger urban prices that sellers may receive in larger markets, or with more intermediaries competing for output.[21] Finally, decreasing transport costs by 50% is roughly meant to capture increasing the speed of travel in Kilimanjaro to US standards.

The results from these counterfactuals on adoption and mark-ups are presented in Figure 5, where we calculate kernel densities for the outcomes of interest. Baseline adoption and mark-ups are illustrated in black. Blue is the output price shock, red the transport shock, and green the wholesale price shock. Overall average effects of shocks and averages by district are presented in Table 5. Interestingly, there is basically no movement in mark-ups for anything other than the wholesale price shock. This is because the output price and transport shocks are common across all locations through the bilateral market shares, and as such, there is very little change in probabilities and market shares (conditional on adoption). In contrast, the wholesale price shock has a significant

[20] Clearly, having α's that are negative is due to over-fitting the model on the farmer-side. However, when focusing on the marginal effect output prices on adoption, there is an interesting interpretation outside the scope of the model. Specifically, if farmers are net buyers of maize for consumption and are credit constrained, a higher output price will reduce money available to purchase fertilizer since the money is otherwise going to consumption. This will be an aspect of the model we will build out as we move forward with the project.

[21] The choice of 50% is meant to match the input price shock, but is not far off from the difference in prices from Nairobi to Moshi.

effect on markups since it operates as a direct cost shock to the agrovet, and affects the adoption margin as well.

Moving to the effects of the counterfactuals on adoption, we see in Table 5 that adoption tends to increase with each of the shocks, but to different degrees. The output prices and transport costs shocks each have approximately a 6 pp effect on adoption, which is 10% over baseline. More pronounced is the wholesale price shock, which increases adoption by about 10pp, or 16% over baseline. Again, the transport cost and output prices shocks only affect the average user cost or returns from fertilizer demand through the decision to adopt itself, and there is no direct cost reduction to pass-through to farmers. In contrast, the wholesale price shock directly affects the cost of doing business for the agrovet, and is partially passed along to consumers. While markups rise substantially in response to the wholesale price reduction, the mean agrovet price falls by approximately 42% in response to a 50% input price shock. With the other shocks, the price rises very modestly in response to better buying conditions.

To examine the mean effects of these shocks across different districts within the region, Table 5 reports the average changes in adoption and mark-ups by district. Here we find that the effects of all shocks are amplified on a percentage basis is districts with low adoption to begin with. In some cases (Siha, for example), both the percentage point and percentage effects of the shocks are higher than the overall region. Overall, while the effects of marginal reductions in costs like transport may have intuitive but modest effects on overall adoption in the region, for less developed districts, the effects may be more pronounced.

5 Conclusion

This paper has presented novel evidence on the availability of inputs for farmers in Kilimanjaro, Tanzania, and especially, the role the remoteness plays in access to productivity technologies. Being more remote, as measured by transportation costs and distance from the regional hub in Moshi, is associated with lower adoption of fertilizer, a decreased likelihood of visits by output buying intermediaries, higher retail fertilizer prices, and higher "local" transport costs for farmers to incur in the process of purchasing fertilizer

As Kilimanjaro is a relatively prosperous region, we are continuing field work in other regions of Tanzania. Further, we plan to do extensive work evaluating the sourcing decisions of output buying intermediaries, and how the presence of output buying intermediaries ultimately affects the decision by farmers to adopt fertilizer.

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Table 1. Summary statistics on villages in Kilimanjaro region

Panel A. Villages (N = 570)	
Population	2842.15
	(1882.22)
Distance to nearest market center (km) - Google	5.69
	(9.10)
Time for round-trip journey to nearest market center (mins) - Google	21.28
	(32.48)
Time for round-trip journey to nearest market center - surveys	40.43
	(33.03)
Cost of round-trip journey to nearest market center (USD) - surveys	1.59
	(1.94)
Distance to Moshi (km) - Google	65.76
	(52.52)
Round-trip travel time to Moshi (mins) - Google	177.23
	(117.92)
Round-trip cost of travel to Moshi USD - surveys	4.69
	(3.76)
Panel B. Road Quality (N = 570)	
Measurement of roads in field	
Percent of road that is:	
Paved	0.27
Dirt	0.35
Gravel	0.37
Cost of trip from market center to village (paid by enumerator)	0.91
	(1.19)
Google estimates	
Travel speed on major roads - km/hr (Google)	49.5
Travel speed on feeder roads and rural roads - km/hr (Google)	30.6
Panel C. Farmers (N = ?)	
Used chemical fertilizer in 2015 long rains season	0.55
If yes, quantity used	55.62
Used improved seeds in 2015 long rains season	0.83
If yes, quantity used	8.79
Sold maize after 2015 long rains season	0.38
If yes, quantity sold	850.17
	(1108.15)
Sold maize to an agent	0.19
If yes, quantity sold	1000.33
	(1213.97)
Acres of land	2.72
	(3.65)
Harvest output (kg)	803.37
	(1090.20)
Value of harvest output (USD, at mean 2015 long rains prices)	180.71
	(245.23)

Notes: Standard deviations in parentheses.

Table 2. Relationship between remoteness and village-level market access

	(1)	(2)	(3)	(4)
	Mean of dependent variable	Transport surveys	Google	
		Log (cost to Moshi)	Log (hours to Moshi)	Log (km to Moshi)
Panel A. From village GPS and agrovet census (N=570)				
Minimum travel-cost adjusted price for 50 kg of Urea[1]	21.91	1.73	2.14	1.66
	(3.09)	(0.15)***	(0.15)***	(0.11)***
Distance to obtain minimum travel-cost adjusted price (km)	10.36	2.93	3.39	2.48
	(10.90)	(0.59)***	(0.61)***	(0.46)***
Cost of travel to obtain minimum travel-cost adjusted price (km)	2.36	0.67	0.77	0.57
	(2.49)	(0.13)***	(0.14)***	(0.11)***
Has at least 1 agrovet within 5 km of village	0.62	-0.08	-0.08	-0.06
	(0.48)	(0.03)***	(0.03)***	(0.02)***
Has at least 1 agrovet within 10 km of village	0.85	-0.07	-0.07	-0.06
	(0.36)	(0.02)***	(0.02)***	(0.02)***
Has at least 1 agrovet within 20 km of village	0.97	-0.03	-0.02	-0.02
	(0.17)	(0.01)***	(0.01)**	(0.01)***
Number of agrovets within 5 km of village	3.61	-0.83	-1.55	-1.13
	(4.51)	(0.25)***	(0.25)***	(0.19)***
Number of agrovets within 10 km of village	8.10	-1.47	-2.57	-1.80
	(9.32)	(0.51)***	(0.53)***	(0.4)***
Number of agrovets within 20 km of village	21.25	-5.92	-7.37	-5.22
	(17.23)	(0.91)***	(0.94)***	(0.72)***
Panel B. From farmer surveys (N=109)				
At least one agent visited village	0.53	-0.09	-0.11	-0.08
	(0.50)	(0.06)	(0.06)*	(0.05)*
Average number of agents visiting farmers in village	0.64	-0.24	-0.30	-0.21
	(0.90)	(0.1)**	(0.11)***	(0.08)**
Average village output price (per kilogram)	0.23	0.02	0.01	0.01
	(0.06)	(0.01)**	(0.01)	(0.01)

Notes: In Column 1, standard deviations are in parentheses. In Columns 2-4, standard errors in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

[1]Travel costs imputed from transport surveys and Google maps. We assume farmers buy a 50 kg bag in one trip (enough for 1 acre), the modal amount observed in our data, and must incur the cost of 3 trips to the retailer (a round-trip for herself, plus a trip for the bag of fertilizer).

Table 3. Relationship between remoteness and fertilizer adoption, maize sales, and farmer characteristics

	(1)	(2)	(3)	(4)
	Mean of dependent variable	Transport surveys	Google	
		Log (cost to Moshi)	Log (hours to Moshi)	Log (km to Moshi)
Panel A. Agricultural outcomes				
Used chemical fertilizer	0.55	-0.14	-0.17	-0.14
		(0.05)***	(0.05)***	(0.04)***
Quantity of chemical fertilizer used	27.47	-13.41	-15.24	-11.53
	(56.77)	(3.68)***	(3.45)***	(2.56)***
If used, distance traveled to agrovet (km)	5.91	1.91	1.14	0.75
	(13.47)	(1.41)	(1.30)	(0.95)
Used improved seeds	0.83	-0.08	-0.08	-0.06
		(0.03)***	(0.03)***	(0.02)***
If used: quantity of improved seeds used	6.50	-1.54	-1.52	-1.06
	(8.53)	(0.52)***	(0.54)***	(0.4)***
Harvest output (kilograms)	803.37	-211.34	-266.83	-187.05
	(1090.20)	(60.51)***	(69.84)***	(52.67)***
Value of harvest output at average regional price	180.71	-47.54	-60.02	-42.07
	(245.23)	(13.61)***	(15.71)***	(11.85)***
Agent visited homestead	0.25	-0.09	-0.10	-0.07
		(0.03)***	(0.04)***	(0.03)**
Number of agents visited	0.60	-0.24	-0.26	-0.19
	(1.32)	(0.08)***	(0.1)**	(0.08)**
Sold maize	0.38	-0.13	-0.13	-0.09
		(0.03)***	(0.04)***	(0.03)***
Quantity sold (kg)	516.77	-239.60	-231.73	-164.30
	(958.04)	(60.24)***	(70.55)***	(53.42)***
Sold maize to an agent	0.19	-0.07	-0.07	-0.05
		(0.02)***	(0.03)**	(0.02)**
Quantity sold to agents (kg)	739.16	-143.13	-156.29	-99.79
	(1094.62)	(85.26)*	(86.8)*	(65.49)
Farmer ever buys maize	0.39	0.16	0.17	0.12
	(0.49)	(0.03)***	(0.03)***	(0.03)***
Quantity purchased in typical year	126.93	73.77	73.00	55.16
	(243.76)	(15.33)***	(17.45)***	(13.34)***
Panel B. Other farmer characteristics				
Age	49.82	-3.00	-3.38	-2.55
	(13.99)	(0.81)***	(0.84)***	(0.62)***
Married	0.78	0.01	0.02	0.02
	(0.41)	(0.02)	(0.02)	(0.02)
Years of education	7.36	0.00	-0.04	-0.01
	(2.54)	(0.12)	(0.14)	(0.10)
Home has iron roof	0.91	-0.04	-0.03	-0.02
	(0.29)	(0.02)	(0.02)	(0.02)
Walls of home are not mud[1]	0.75	0.00	0.05	0.04
	(0.44)	(0.03)	(0.03)*	(0.02)*
Has cell phone	0.87	-0.03	-0.04	-0.03
	(0.34)	(0.02)	(0.02)*	(0.02)*
Has bank account	0.20	-0.06	-0.03	-0.03
	(0.40)	(0.03)**	(0.03)	(0.02)
Has mobile money account	0.81	-0.05	-0.03	-0.03
	(0.39)	(0.02)**	(0.02)	(0.02)
Acres of land	2.72	0.54	0.30	0.27
	(3.65)	(0.19)***	(0.22)	(0.17)
Household size	5.19	-0.02	-0.02	-0.03
	(2.18)	(0.13)	(0.14)	(0.11)
Has market business	0.22	-0.09	-0.08	-0.06
	(0.41)	(0.03)***	(0.03)***	(0.02)***
Annual total income from non-farming (USD)	364.77	-86.31	-71.01	-56.29
	(836.46)	(60.49)	(56.29)	(43.02)

Notes: N = 563 farmers in 115 villages. In Column 1, standard deviations are in parentheses. In Columns 2-4, standard errors in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

[1]Wall types include brick, cement, stone, and wood.

Table 4. Relationship between remoteness and fertilizer retailer sales, prices, and other characteristics

	(1)	(2)	(3)	(4)
	Mean of dependent variable	Transport surveys	Google	
		Log (cost to Moshi)	Log (hours to Moshi)	Log (km to Moshi)
Panel A. Fertilizer availability, prices, and sales				
Sells Urea fertilizer	0.98	-0.01	0.00	0.01
		(0.04)	(0.01)	(0.01)
Sells DAP fertilizer	0.62	0.19	0.04	0.05
		(0.13)	(0.02)	(0.05)
Sells CAN fertilizer	0.15	0.09	0.04	0.07
		(0.12)	(0.02)	(0.05)
Sells NPK fertilizer	0.12	0.25	0.05	0.07
		(0.14)*	(0.02)**	(0.04)
Sells other types of fertilizer[1]	0.34	-0.57	-0.10	-0.19
		(0.11)***	(0.02)***	(0.04)***
Bags of Urea sold	163.99	49.69	30.84	73.52
	(826.88)	(220.03)	(48.02)	(97.47)
Total bags of fertilizer sold	337.21	162.23	68.61	166.79
	(2121.97)	(570.77)	(125.95)	(258.14)
Monthly income (USD)	149.85	-143.72	-25.84	-44.08
	(316.46)	(109.16)	(19.53)	(36.56)
Prices and markups				
Retail price for 50 kilograms, Urea only	23.74	2.98	0.26	0.39
	(3.27)	(1.03)***	(0.21)	(0.45)
Wholesale price for 50 kilograms, Urea	20.01	0.35	0.06	0.04
	(1.37)	(0.44)	(0.08)	(0.15)
Retail price for 50 kilograms, all types[2]	25.87	4.06	0.42	0.69
	(5.53)	(0.83)***	(0.16)***	(0.33)**
Wholesale price for 50 kilograms, all types	21.85	0.96	0.11	0.15
	(4.26)	(0.46)**	(0.08)	(0.16)
Panel B. Other characteristics				
Male	0.77	0.30	0.05	0.10
	(0.42)	(0.09)***	(0.02)***	(0.03)***
Married	0.83	0.16	0.02	0.02
	(0.38)	(0.09)*	(0.02)	(0.04)
Years of education	10.11	-3.53	-0.55	-0.96
	(3.41)	(0.9)***	(0.19)***	(0.4)**
Home has iron roof	0.98	-0.07	-0.01	-0.01
	(0.13)	(0.07)	(0.01)	(0.02)
Has cell phone	0.98	0.01	0.01	0.01
	(0.12)	(0.02)	(00)**	(00)**
Has bank account	0.69	0.04	0.02	0.04
	(0.46)	(0.16)	(0.03)	(0.05)
Has mobile money account	0.98	-0.05	-0.01	-0.02
	(0.16)	(0.04)	(0.01)	(0.02)
Acres of land	4.58	-1.82	-0.28	-0.69
	(7.27)	(1.96)	(0.37)	(0.65)
Household size	4.72	1.16	0.34	0.51
	(2.13)	(0.64)*	(0.12)***	(0.23)**

Notes: N = 351. In Column 1, standard deviations are in parentheses. In Columns 2-4, standard errors in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%.

[1]Other types of fertilizer include local varieties SA, Yara, and Minjingu.

[2]

Table 5. Counterfactuals

Panel A. Adoption

	Baseline	**50% higher output price**		**50% lower transport cost**		**50% lower wholesale price**	
Sample/District	Adoption	Adoption	% Change	Adoption	% Change	Adoption	% Change
ALL	0.61	0.67	10.0	0.68	10.6	0.71	16.1
HAI	0.73	0.81	11.6	0.79	9.3	0.81	12.0
MOSHI MJINI	0.84	0.94	11.3	0.92	8.6	0.95	12.1
MOSHI VIJIJINI	0.86	0.91	6.0	0.91	5.2	0.94	9.5
MWANGA	0.09	0.11	17.0	0.12	36.9	0.15	65.7
ROMBO	0.56	0.61	7.6	0.62	9.2	0.73	29.7
SAME	0.53	0.6	14.5	0.62	17.1	0.63	20.1
SIHA	0.41	0.47	13.3	0.52	25.4	0.54	31.1

Panel B. Markups

	Baseline	**50% higher output price**		**50% lower transport cost**		**50% lower wholesale price**	
Sample/District	Markup	Markup	% Change	Adoption	% Change	Markup	% Change
ALL	18.0	18.0	0.2	17.9	-0.6	36.1	100.4
HAI	14.7	14.7	0.1	14.6	-0.4	29.5	101.4
MOSHI MJINI	6.1	6.1	0.0	6.1	0.0	12.3	100.4
MOSHI VIJIJINI	12.5	12.5	0.0	12.4	-0.1	25.0	100.7
MWANGA	47.9	48.1	0.4	48.1	0.3	94.6	97.4
ROMBO	22.9	23.0	0.1	22.9	-0.3	45.7	99.5
SAME	17.9	17.9	0.4	17.6	-1.7	36.1	101.9
SIHA	14.9	14.9	0.1	14.9	-0.4	30.0	100.7

Figure 1. Map of Survey Region and Villages

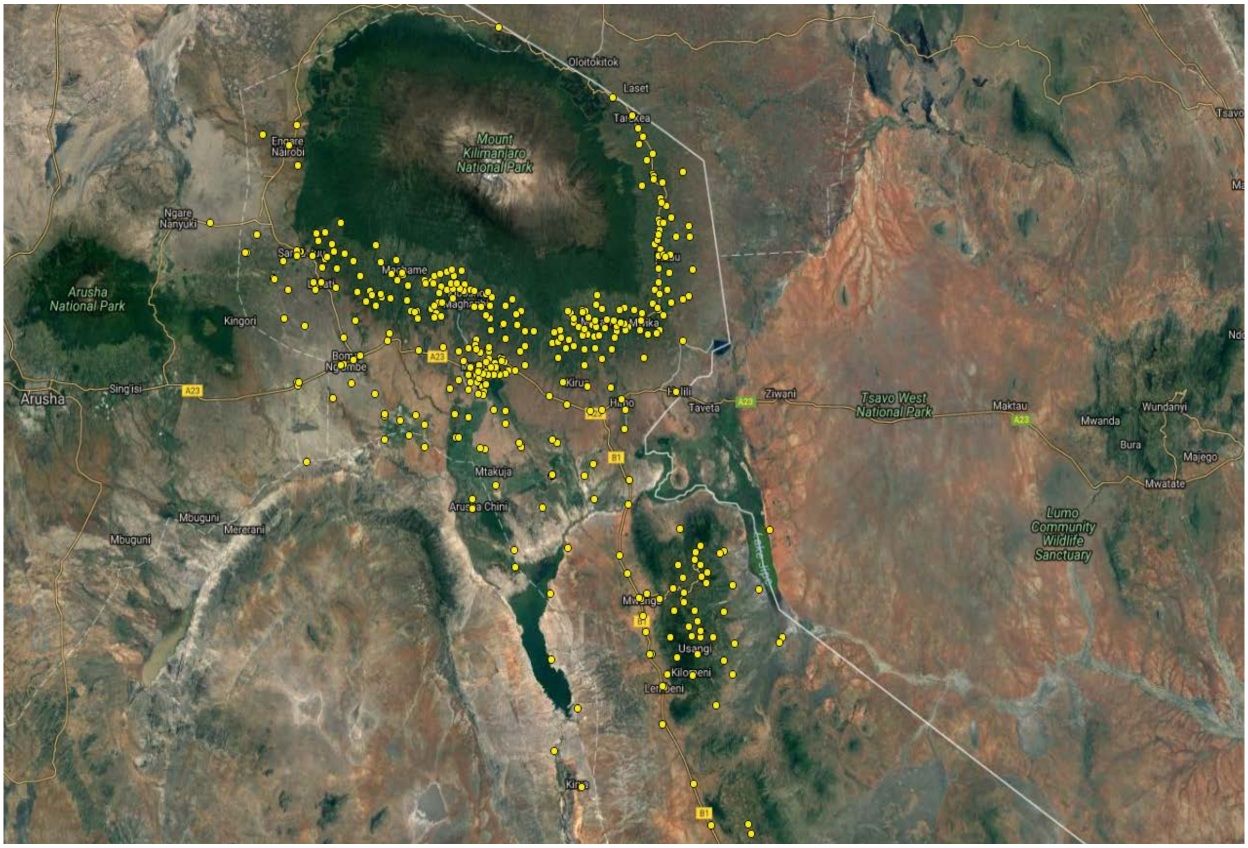


Figure 2. CDF of distance farmers travel to purchase agrovet

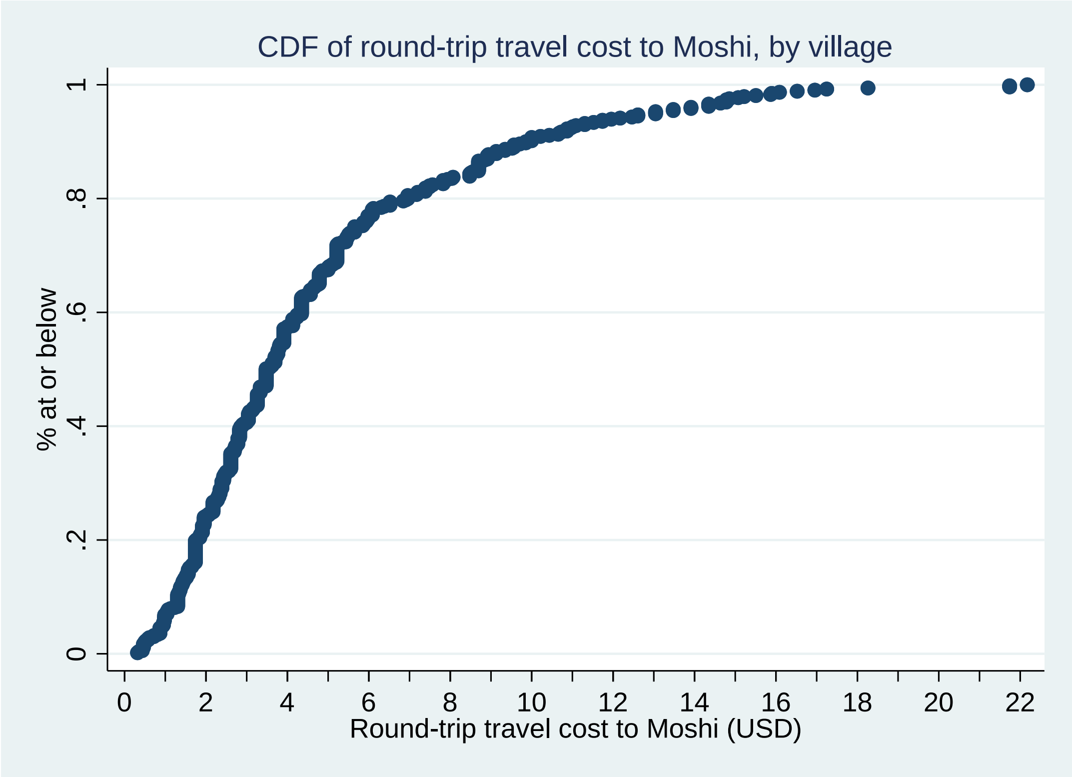


Figure 3. CDF of distance farmers travel to purchase agrovet

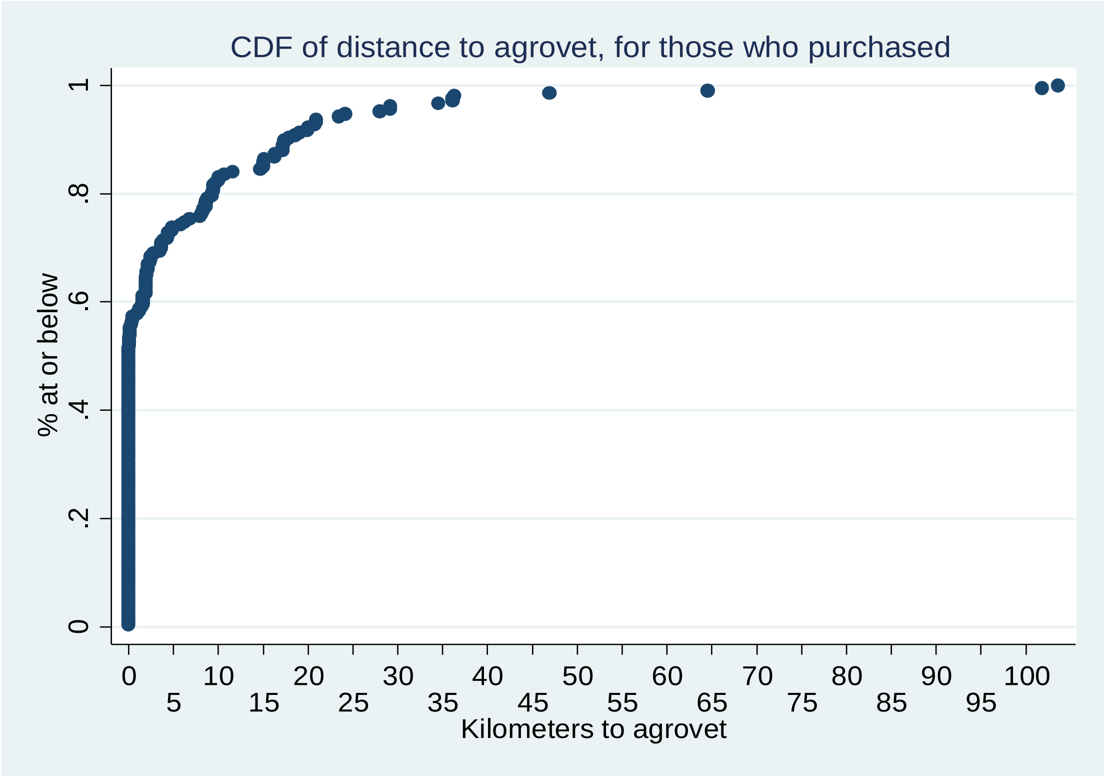


Figure 4. Retail prices, wholesale prices, and markups for Urea

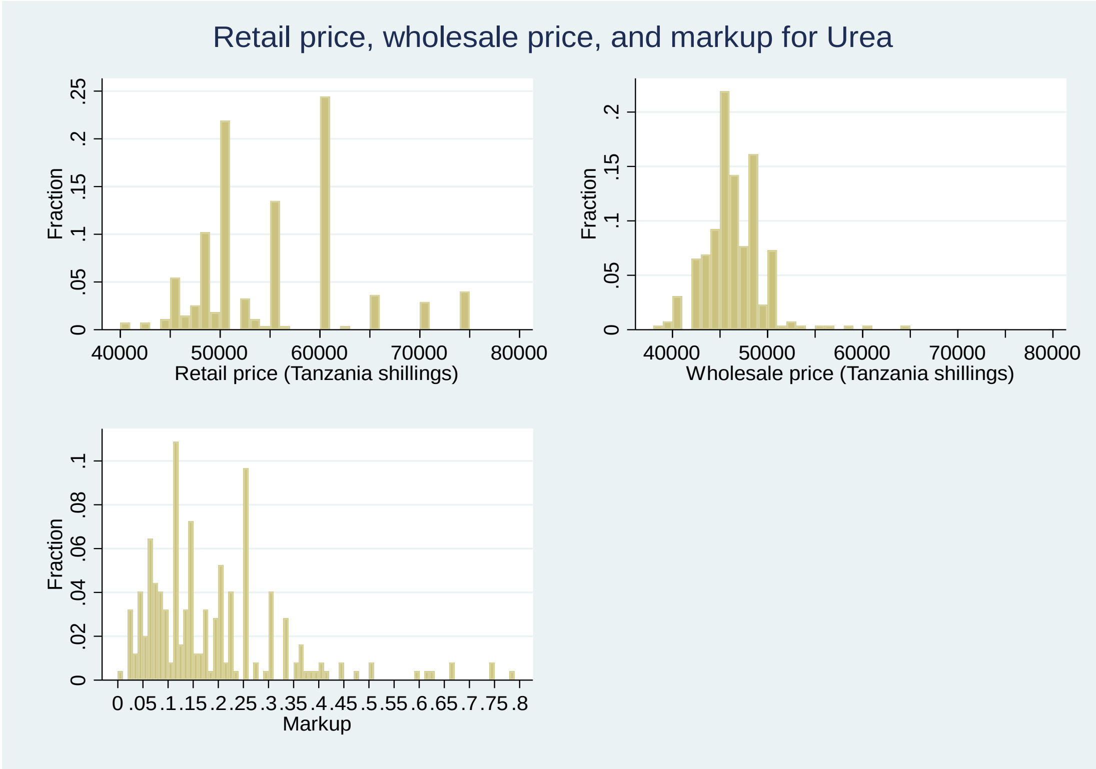
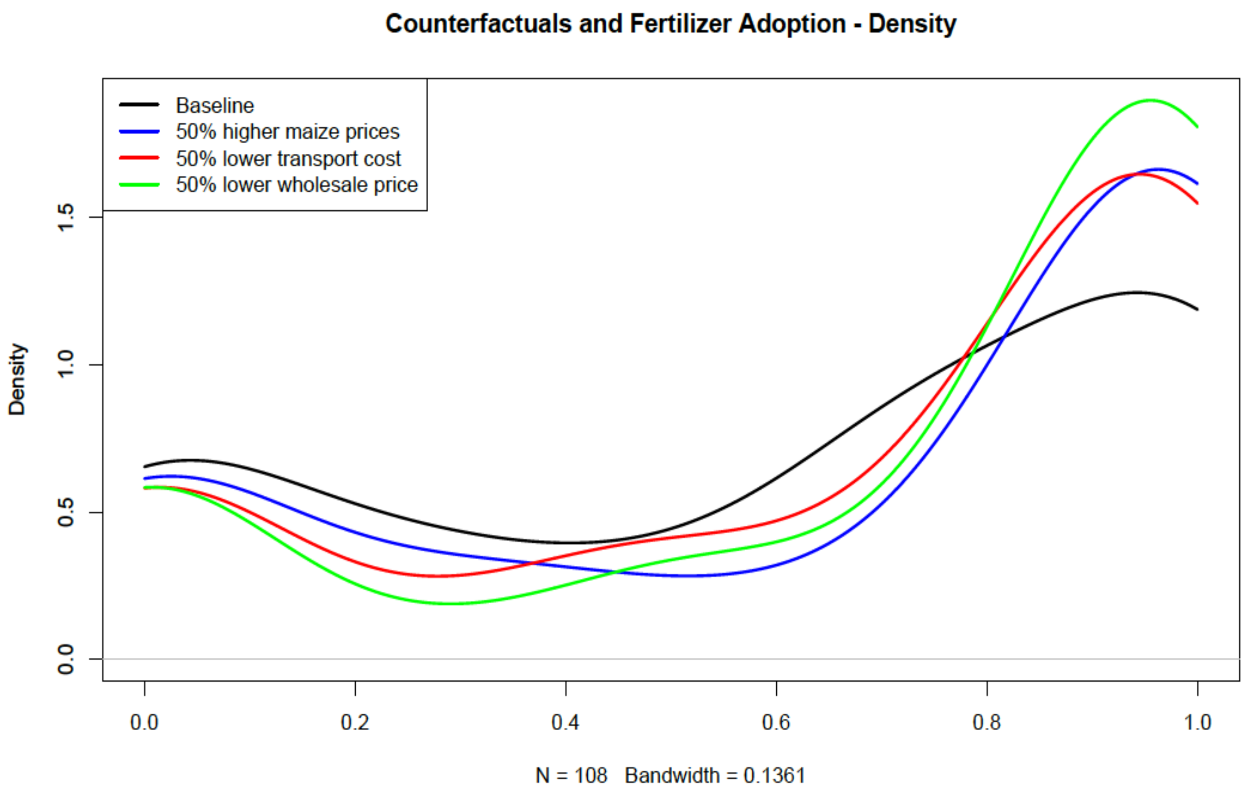
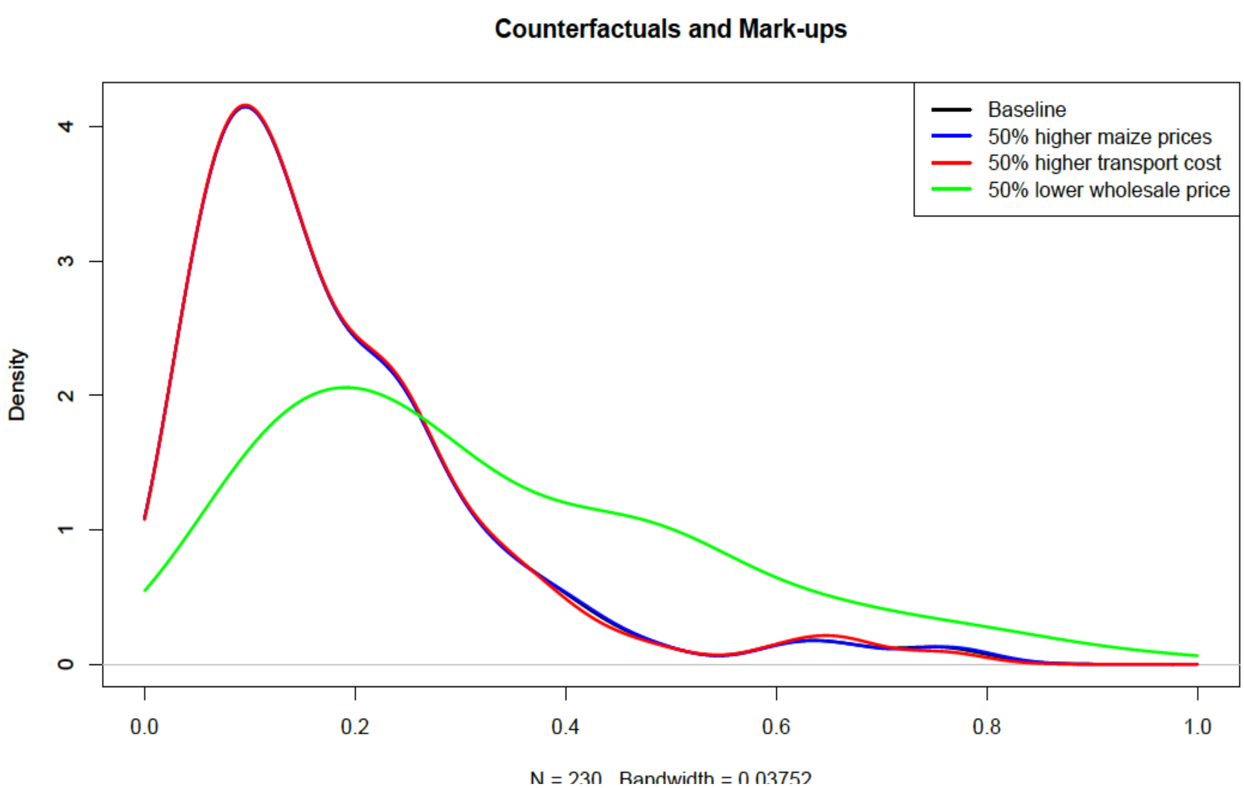


Figure 5. Counterfactual Densities - Mark-ups and Adoption





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