# Going the Extra Mile: Farm Subsidies and Spatial Convergence in Agricultural Input Adoption*

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**Abstract**

Many countries subsidize agricultural inputs but require farmers to travel to retailers to access them, just as for normal purchases. What effect do travel costs have on subsidy take-up and input usage, particularly for remote farmers? We analyze Malawi's Farm Input Subsidy Program (FISP), and find that travel-cost-adjusted prices are substantially higher in remote areas, due almost entirely to increased travel costs. Nevertheless, subsidy redemption is nearly universal and only modestly lower in remote areas, suggesting that these travel costs are not enough to dissuade redemption. We evaluate the effect of FISP on spatial adoption, by utilizing a policy change which centralized beneficiary selection. While we find a sizeable remoteness gradient for non-beneficiaries, there is no such gradient for beneficiaries. Our results demonstrate that subsidy programs may narrow spatial inequities.

*JEL Codes:* O12, O13, Q12, Q16, Q18

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# 1 Introduction

Poor transportation infrastructure impedes access to input markets (World Bank 2007; World Bank 2017), lowering input usage and agricultural productivity in remote areas (Aggarwal et al. 2024a; Minten et al. 2013; Shamdasani 2021). To reduce these spatial inequalities, policy and research have focused on reducing transport costs, for example via road construction (Aggarwal 2018; Brooks and Donovan 2020; Gebresilasse 2023; Porteous 2019). In this paper, we examine the spatial properties of another policy instrument: input subsidies. While input subsidies are widely used to spur agricultural productivity,[1] they are usually aimed at improving general input usage, rather than to mitigate spatial gradients.

*A priori*, input subsidies should generate spatial convergence, since remote farmers are less likely to already be using inputs. However, in practice, many subsidy programs require beneficiaries to procure inputs at retail or specialized locations that may be located far away. For example, in the setting of this study, the Farm Input Subsidy Program (FISP) in Malawi, beneficiaries received coupons redeemable only at selected retailers; thus, remote farmers still had to incur transport costs to reach distant agro-retailers. It is, therefore, possible that a subsidy such as this could leave the distance gradient unchanged or may even worsen it if subsidy take-up is sufficiently elastic to travel costs.

In this paper, we rigorously study spatial differences in FISP prices, redemption, and input usage using survey data of 2,664 maize farmers in 300 villages in 2 districts of Malawi, as well as surveys of all agricultural input dealers in the area. The data covers the agricultural seasons from 2017-18 to 2019-20. At the time, the subsidy was worth about \$56 (a 75% discount), which is a substantial sum for this population, and was disbursed in the form of paper coupons, which had to be presented for redemption at participating local retailers.

We follow Aggarwal et al. (2024a) to construct a measure of market access for fertilizer by calculating the travel cost-adjusted price farmers face. We collected fertilizer prices at

[1] At least 10 countries in this region have large-scale subsidy programs, which form their largest agricultural outlay (Dorward et al. 2004; Jayne et al. 2018).

the universe of agro-input dealers in the region, and used Google Maps API to calculate distances from each of the 300 villages in our sample to every retailer. We estimate travel costs using a multinomial choice model in which we regress the revealed choice of retailer on a location-specific fixed effect (capturing price and unobserved quality) and the distance from the farmer's village to that location (measured separately by road quality). We then calculate travel cost-adjusted prices for every location, imputing travel costs using the model, and find the minimum price a farmer faces. We find that the average travel cost is substantial: \$5.4 for market fertilizer and \$9.1 for subsidized fertilizer (the larger value for subsidized fertilizer is because only certain retailers participate in the program, so farmers have to travel farther to reach them). Because the subsidy reduces the retail price by 75%, the implied ad-valorem travel cost, already sizeable for unsubsidized fertilizer (19%), is enormous for subsidized fertilizer (over 100%).

We find substantially higher prices in more remote areas: a standard deviation increase in remoteness is associated with a \$1.9 increase in the travel-cost-adjusted price of unsubsidized fertilizer (5.5%), and since not all locations sell subsidized fertilizer, a \$3.8 increase in the price of subsidized fertilizer (21%). This gradient is almost entirely driven by travel costs, as retail prices have little spatial dispersion in our sample (the standard deviation in retail prices is \$0.56, less than 2% of the mean price). However, somewhat surprisingly, we find only modestly lower subsidy redemption in more remote areas: subsidy redemption is nearly universal in both remote and proximate locations, and declines only modestly with distance.

Nearly universal redemption implies that subsidy receipt should largely eliminate any gradient in fertilizer usage. Historically, FISP had been officially targeted towards disadvantaged farmers, and beneficiary selection was delegated to local chiefs, who often directed households to share inputs with one another (see papers such as Basurto et al. 2020 for more information). However, in 2017-18, the program was redesigned to a centralized allocation controlled by the Ministry of Agriculture. We examine this policy for the 2017-18, 2018-19, and 2019-20 seasons.[2]

Officially, the allocation was meant to be random; however, it is unclear if it was so in practice. Beneficiaries were selected from a list of farming households – but we do not have access to this list itself. Instead, we have only our household survey data, which may depart from the farming list for several reasons. Among the households in our data, we find that older and larger households, those related to the chief, and those who received the program in a prior year are more likely to receive the subsidy. This does not necessarily mean that the program was implemented non-randomly by the government – it is possible that there were selection into the beneficiary list in the first place, or that the original allocation might have been later undone by other local actors.[3] However, it is clear that a direct comparison between FISP beneficiaries and non-beneficiaries is not appropriate in this setting.

Nevertheless, our main research question is not about the direct effect of FISP itself, but rather to examine the effect of FISP on the remoteness-input adoption gradient. The key identifying assumption therefore is whether selection into FISP varies differentially with remoteness. We find no evidence of such differential selection. In addition, we perform a placebo test where we examine how contemporaenous input usage varies with future FISP receipt, and find a small insignificant coefficient on the extensive margin, and a small, negative, modestly significant coefficient on quantities (which, if anything, will attenuate effects).

Our preferred specification is a difference-in-difference with household fixed effects, utilizing 3 years of data on FISP receipt and fertilizer usage. In the cross-section, i.e., without using household fixed effects, we find that a standard deviation of remoteness is associated with lower input usage of 10 percentage points on the extensive margin and 15% on the intensive margin among non-FISP beneficiaries. However, this gradient is reduced by 7 percentage points and 10 kg, respectively among FISP beneficiaries, suggesting that spatial

[2]Although we collected data for 2020-21 as well, we do not use it because in that year FISP was rebranded as AIP (Affordable Inputs Program) and became universal.

[3]One particular possibility is that some households might have been "split" into two households and listed twice, and such splitting may have been more likely for certain groups (such as older, larger households, or elites)

disparities are dramatically smaller under FISP.

While there is a large literature examining the causal effects of input subsidies,[4] as well as a sizeable literature on FISP specifically[5], our paper is differentiated by its focus on examining the effect of a subsidy on spatial adoption patterns. In this sense, our paper relates to a large and growing literature on market access and agricultural input adoption. Papers in this literature have tried to causally measure the impact of distance on input use via interventions that directly reduce transport costs, such as road-building or input fairs near villages; see Porteous (2019), Gebresilasse (2023), Aggarwal et al. (2024b) and Dillon and Tomaselli (2024). We extend this literature by studying the interplay between market access and technology adoption in the context of subsidized inputs. In doing so, we also contribute to work on the costs of accessing subsidies, which documents large effects of small co-pays on take-up of health products (i.e. Cohen and Dupas 2010, Ashraf et al. 2010, Chang et al. 2019, Kremer and Miguel 2007); though we focus on how consumer decisions are impacted by travel costs rather than by purchase price at the point of sale.

Our paper is also related to a long-standing literature on overcoming "ordeals" in order to access public goods and subsidies (Nichols et al. 1971). Typically, these ordeals impose non-monetary or "inconvenience" costs, such as standing in line or filing paperwork, and not as pecuniary transaction costs, such as those incurred on transportation. However, as we document in Aggarwal et al. (2024a), in Tanzania, the implied trade costs of procuring fertilizer for farmers are much larger than the measured pecuniary costs, suggesting the presence of other costs, such as the opportunity cost of time or uncertainty related to stock-outs, which may be similar to ordeals. Such ordeals can serve a useful targeting function as only those who sufficiently value the good will overcome the ordeal to acquire it (Sylvia et al. 2022; Dupas et al. 2016). However, when the good in question is universally valued, ordeals could exclude legitimate beneficiaries (see Deshpande and Li (2019) in the context of US

[4]See, for example, Carter et al. 2013, Carter et al. 2021, Fishman et al. 2022 and Gignoux et al. 2023

[5]For example, see Arndt et al. (2016), Dorward et al. (2004), Chirwa et al. (2011), Holden and Lunduka (2012), Chirwa and Dorward (2013), Lunduka et al. (2013), Kilic et al. (2015), Ricker-Gilbert and Jayne (2017), Ricker-Gilbert et al. (2011), and Basurto et al. (2020).

disability benefits, Nagavarapu and Sekhri (2016) in the context of publicly distributed grain in India, and Carrillo and Ponce Jarrín (2009) in the context of cash transfers in Ecuador). A recent related paper is Dupas and Jain (2024), who demonstrate gender difference in healthcare utilization in India, despite such care being nominally free, due in part to gender differences in travel costs. Even when take-up is inelastic to the costs of overcoming the ordeal, the mechanism may end up being regressive by imposing higher costs on those who are disadvantaged, as is the case in our findings about FISP, as well as those of Carrillo and Ponce Jarrín (2009) in regards to cash transfers in Ecuador.

# 2 Background and Data

## 2.1 Institutional Context

Malawi has a unimodal rainfall pattern with a single rainy season which runs from November to April/May.[6] Between 2004 and 2020, the Ministry of Agriculture provided input subsidies via the Farm Input Subsidy Program (FISP). While FISP reached about two-thirds of farming households in earlier years, the program was scaled down over time. Only about 15% of our sample received the subsidy in any year between 2014 and 2020.

Traditionally, local leaders had authority over beneficiary selection. However, this system was shown to be subject to nepotism and elite capture (Kilic et al. 2015, Lunduka et al. 2013, Holden and Lunduka 2012). In response, in 2017, the program was transitioned to centralized beneficiary selection, using a list of eligible farmers.[7]. Thus, all local discretion over the assignment of coupons was, in principle, removed, and the initial selection of beneficiaries was exogenous to the local community.

During the period that we study (2017/18-2019/20), FISP subsidized 4 inputs - 50 kg

[6] See FEWSNET for the typical crop calendar.

[7] See Centre for Development Management and Farmers Union of Malawi (2017) for a discussion of this policy change.

each of NPK and Urea fertilizer, 5 kg of hybrid maize seeds,[8] and 2 kg of hybrid legume seeds. The subsidy provided a discount of 75% on the market value of the package (approximately $75), meaning that a beneficiary would have to pay about $18.

Farmers received these coupons as a single leaf with 4 detachable coupons, one for each input, and farmers could redeem as many or as few as they wished. However, each individual coupon had to be redeemed in its entirety, which is likely why there was widespread sharing of subsidized inputs. Because the subsidy is generous, take-up is nearly universal: 95% of beneficiaries in our sample redeemed their coupon.

These coupons can be redeemed at select agro-input dealer locations. Dealers who wish to participate in the program apply and are selected by the government. Participating retailers are typically larger chains with multiple locations, rather than smaller local retailers with a single location. To access subsidized inputs, farmers present the coupon as well as the co-pay amount at the retailer, some of which may be fairly distant from the farmers' home villages. Retailers can present the coupons thus received to the district administration and get directly reimbursed for the subsidized amount, plus a small handling fee.

## 2.2 Data

As part of an evaluation of unconditional cash transfers, we administered surveys with 10 randomly selected households each in 300 villages in Chiradzulu and Machinga districts in Southern Malawi.[9] Baseline surveys were completed with 2,944 households in April-July 2019. From this sample, we drop 380 farmers because they do not own land (one of the criteria for being listed), do not grow maize in any of the three seasons for which we have data (the focus crop for FISP), or because they were either the spouse or child of the village chief (since prior work has shown evidence of nepotism towards the family of the chief). In our analysis, we only include seasons in which farmers grew maize. Thus, our final sample for this analysis is 2,564 farmers (87% of the baseline sample) and 6,827 farmer-year pairs(thus

[8] Farmers could instead use this voucher for 7 kg of open-pollinated variety maize or sorghum seeds.

[9] See Aggarwal et al. (2025) for more details about the sampling strategy.

each farmer appears 2.7 times).

In the baseline, we collected information on input usage and harvest for the 2017-18 season, and input usage for the 2018-19 planting season; in the endline, we collected information on the 2018-19 harvest and the entire 2019-20 season. Our surveys collected standard demographic data, as well as information about FISP receipt, redemption, and sharing. We collected detailed questions on input usage (from all sources) and harvest. To precisely measure travel cost-adjusted prices, we included questions on the location and cost of purchasing inputs, including travel costs.[10]

For information on the price and purchase location for fertilizer, we conducted a census of agro-input sellers in the area (encompassing the 2 study districts as well as 7 contiguous districts - Balaka, Blantyre, Mangochi, Mulanje, Phalombe, Thyolo, and Zomba).[11] The census collected basic information on the availability and price of seeds and fertilizer. After the census, we followed up with detailed surveys with each retailer, which took 1-1.5 hours to complete. The census identified a total of 466 retailers that sold fertilizer, 431 of which completed the longer survey (92%).

The census was conducted in March 2019 in our study districts and in November 2019 in the remaining districts. The longer surveys were conducted in November-December 2019. Because the latter survey was conducted in a shorter temporal frame, we rely on this as our primary measure of prices (to minimize temporal variation); in addition, the timing of this data collection was at the beginning of the planting season, when farmers would normally be purchasing fertilizer. For the 35 agro-dealers that completed the census but not the longer survey, we use the prices reported in the census. We examined this database for outliers and found data errors for 8 retailers (1.7% of the sample), as they had prices far from the mean. We correct these using the law of one price as 7 out of the 8 were located in markets with at least one other agro-dealer.[12]

[10]For the specific questions that were used, please see the posted questionnaires on the authors' websites.

[11]We include neighboring districts because farmers near district borders may travel across them to access inputs.

[12]In our data, the law of one price holds within locations with multiple agro-dealers: the standard

We show agro-dealer summary statistics in Table A1. The average agro-dealer has been in business for 6 years and 47% are authorized to sell under FISP. The average operation is fairly large, with $33,000 in revenue in the previous year, which is more than 50 times the national per capita income; however, there is sizeable heterogeneity in size. Agro-dealers almost universally sell NPK and Urea, the most common forms of fertilizer in Malawi.

# 3 Market access, remoteness and prices

Our analysis exploits variation in the subsidy (and hence input usage) to extend Aggarwal et al. (2024a), which examined correlations between remoteness, market access, and input usage. We use many of the same variable definitions and regression specifications as in that work. In this section, we briefly describe these concepts (and refer the reader to our prior paper for an extended discussion).

## 3.1 Defining market access and remoteness

Similar to Donaldson and Hornbeck (2016), we define market access in terms of distance to local population centers, Blantyre, Lilongwe, and Zomba, the three biggest cities in the country. Of these, Blantyre and Zomba are the closest market towns for our sample (the median distance to Zomba is 44 km and that to Blantyre is 34 km). The specific measure is:

$$MA_v = \sum_h \tau_{hv}^{-\theta} pop_h \tag{1}$$

where $pop_h$ is the population of the hub, and $\tau_{hv}^{-\theta}$ is the elasticity-adjusted trade costs of reaching each hub. We measure $\tau_{hv}$ from surveys that asked about the cost of travel to purchase fertilizer.[13] For $-\theta$, we appeal to the substitution elasticity across agro-retailers

deviation of the price within a location is only 10% of the mean.

[13]In our surveys, we asked farmers for the cost of travel to a retailer, including (1) the cost of traveling themselves as a passenger, and (2) the cost of transporting the purchased bag of fertilizer back home. On average, farmers report that a bag costs about 40% as much as a passenger. We estimate the cost per km

we estimated in Tanzania (-7.9).[14] We then standardize the remoteness measure to have mean 0 and standard deviation 1 (and invert the sign of $MA_v$ to be negative, so that it measures remoteness rather than market access). Note that market access is indexed at the village-level $v$, rather than by farmer; this is because much of the variation in distance is across rather than within villages, and because we have found Google Maps API information to not be reliable *within* small rural villages.

As expected, remote villages differ from proximate ones on several dimensions: Table A2 shows the relationship between farmers' characteristics and our measure of market access. We find several significant correlations: farmers in more remote villages are more likely to be related to the local chief, have fewer years of education, and are less likely to have received FISP in the prior year. In addition, remote villages have higher productivity as measured by FAO-GAEZ agricultural productivity measures.[15] As discussed later, to account for these differences, we use household fixed effects in our main specifications.

## 3.2 Agrodealer choice and estimating travel costs

In prior work in Tanzania (Aggarwal et al. 2024a), we find that model-estimated travel costs track farmer behavior more closely than do costs that rely on pecuniary costs only; we therefore rely solely on model-estimated costs in this paper. As mentioned in Section 2.2, our surveys with agro-dealers give us the universe of prices in the area. We then use Google Maps API to estimate driving times and distances from every village in our sample to every agro-dealer, and use the road names for each segment of the journey to map to a national classification of road type (paved, secondary, etc). In our survey, we asked respondents

using GPS data, and use this to impute costs to all possible retailers.

[14]Here, we backed out structural parameters from an equilibrium of spatial demand and agro-retailer supply. Doing this required survey data from a representative sample of farmers, which we do not have in the current study (since villages were selected based on characteristics such as size). So, we instead rely on our published work for these parameters.

[15]The FAO-GAEZ measures are based on nine datasets, spanning weather, geography, population, and grid-level livestock and agricultural area and production data. Using these, a ratio of actual and potential yields for two varying levels of inputs - high and low - is calculated. The two input levels do not depend on observed input choices; instead, varying levels of agricultural practices and resources are considered.

about every instance in which they purchased inputs, the name and location of the relevant agro-dealer and the cost of travel (as well as other pertinent details of the transaction, such as the price, quantity, and whether a FISP coupon was used). However, many farmers did not accurately recall the name of the retailer, and thus the estimation of trade costs is based instead on the location of purchase (which people did recall). Overall, there are 184 agrovet-locations that farmers may choose from in the model, and weigh the distances to get to each against their prices and other attributes.

We estimate trade costs using a multinominal logit (similar in form to Eaton and Kortum 2002), where farmers choose the location of fertilizer purchase based on price, quality, and bilateral ad-valorem trade costs. The outcome is whether farmer $f$ on trip $t$ traveled from village $i$ to agrovet location $v$ to buy inputs. For the trade costs between $i$ and $v$, we assume that the ad-valorem rate is a function of distance traveled on different road types (i.e. main roads and rural roads). For further technical details, see Appendix C.[16]

To measure baseline trade costs, we use a sample of farmers who did not receive FISP, and farmers who received FISP but did not use it on a particular trip. We do this because FISP is nearly universally redeemed, but is only offered at certain retailers; therefore, non-FISP purchases offers a richer variety of choices for farmers to make (including the option to not buy at all). The results from the estimation (presented in Table C1) indicate that rural roads have a higher impact on ad-valorem costs than main roads. Specifically, a one km increase in main road travel increases the ad-valorem trade cost by roughly 1.8%, while a one km increase in rural road travel increases costs by 2.6% (i.e. the marginal effect of rural road travel is 45% greater). To calculate a dollar value, we use the retail price and apply the estimated coefficients to recover the unit-value of trade costs.

[16]This discrete choice estimation is similar to Kremer et al. 2011, who use distance to local springs to quantify the willingness to pay for protections for water quality. The main difference with our work is that they do not adopt a within-destination approach since that would absorb the water sanitation treatment by destination. We use destination dummies to absorb all observed and unobserved factors in choosing an agro-dealer location, leaving only distance variation to explain choices.

### 3.3 Travel cost-adjusted prices

We now turn to calculating the travel cost-adjusted price farmers face at every possible location. The farmer's best option is the location at which this cost is minimized:

$$p_v^{min} = \min_j \{r_j + c_{vj}\} \tag{2}$$

where $r_j$ is the price at agro-retailer $j$ and $c_{vj}$ is the cost of traveling from village $v$ to agro-retailer $j$, and returning with a bag of fertilizer.

Figure A1 plots price distributions showing how the decision rule affects calculated price dispersion. First, Panel A shows the unconditional distribution of subsidized FISP prices at all 153 agro-retailers in the censused area that accept FISP. The mean price is \$10.5 with a standard deviation of about \$3. However, when we implement decision rule (2), we find that only 12 retailers are chosen. Eight of these are located within the study districts (out of 65 total ag-dealers in those districts), and 4 outside (all in the hubs of Blantyre or Zomba). Panel B shows prices for those 12 retailers. As expected, the mean price is lower than in the full sample (\$8.75) and the standard deviation is much smaller (\$0.56). Thus retail price heterogeneity is minimal under this decision rule, and variation in travel cost-adjusted prices is driven by variation in travel costs.[17]

Figure 1 plots the distribution of travel cost-adjusted prices for the lowest-cost option for each village. Despite the modest variation in retail prices, there is clear heterogeneity after accounting for travel costs: the travel cost-adjusted price at the 90th percentile is \$24.7 compared to \$10.7 at the 10th percentile. The average retail price is \$8.75 (SD \$0.56), while the average travel cost is \$9.1 (SD \$9).

[17]Figure A2 shows a similar figure for the *retail* price. Here in Panel A, we find an unconditional mean and standard deviation of \$31.13 and \$3 for the universe of shops in the area. In Panel B, we find that only 20 retailers are chosen by the decision rule (17 within the study area), and the mean and standard deviation are \$28.9 and \$0.5.

## 3.4 The relationship between remoteness and market access

Table 1 shows the relationship between remoteness and various measures of access to NPK fertilizer, the most widely available input, along with Urea.[18] In Panel A we show summary measures of access to retailers. We find that 88% of villages have at least 1 input retailer within 10 km; however, since only a subset of retailers participate in FISP, only 62% of villages have at least 1 retailer accepting FISP within 10 km. The average distance to the nearest retailer is 5.8 km for market fertilizer, and 10.1 km for FISP.

We observe a large remoteness penalty: an additional standard deviation in remoteness leads to a 14 percentage point decline in the likelihood of having an agrodealer within 10 km of the village (and an 11 percentage point decline in the probability of a retailer that accepts FISP). The distance to the nearest agro-retailer also increases substantially: every standard-deviation of remoteness adds 1.9 km (mean 5.8 km) for market fertilizer and 3.6 km (mean 10.1 km) for FISP fertilizer, i.e., about a 33% increase.

We turn to analyzing prices in Panels B1 for market fertilizer, and B2 for FISP fertilizer. For both, we first show the price inclusive of transport cost (at that agro-dealer for each village where the travel-cost adjusted price is minimized), and then decompose the price into the retail price and the travel cost. For market fertilizer, the average minimum price is \$34.3, with a standard deviation of \$4.5. On decomposition, we see that \$29 of this is the retail price, with a small SD of \$0.6. To this, \$5.4 gets added due to travel costs (i.e. 18.6% ad valorem at the mean, with a large SD of \$4.4), leading to an effective price of \$34.3. In the regression in Column 2, we see that 1 standard deviation increase in remoteness is associated with a substantial increase in this cost (of about \$2 per SD, or 5.5%), coming almost entirely from travel costs.[19]

For FISP fertilizer, we find that while farmers only pay 25% of the retail price, they

[18] The results for Urea are similar and available upon request.

[19] Note that despite Malawi's input market depth, fertilizer prices are much higher than the world price, which was about \$19 for 50 kg of NPK during this period. We observe a retail price of about \$29, nearly 50% higher. Fertilizer prices in Africa are higher than the world price, largely due to travel costs since fertilizer is typically imported. Such costs are substantial in a landlocked country like Malawi.

still incur \$9 in travel costs on average (about 64% more than for retail fertilizer, due to the fact that only some retailers accept FISP). We also see a much larger correlation with remoteness, where 1 SD of remoteness is associated with \$3.9 higher costs, suggesting that retailers in more remote locations are less likely to redeem FISP - another manifestation of the costs of being remote.

## 3.5 Predictions

In the status quo, i.e., without FISP, the expected return to using fertilizer for farmer $i$ in village $v$ is:

$$E[R_{iv}] = E[p_v * (y_{iv}^{fert} - y_{iv}^{0})] - c - \tau_v$$

where $p_v$ is the price of output, and $y_{iv}^{fert}$ and $y_{iv}^{0}$ are yields with and without fertilizer, $c$ is the pecuniary cost of fertilizer and $\tau_v$ is the travel cost. We write $c$ as being unrelated to remoteness (as shown in Table 1), because pecuniary price dispersion is minimal. However, $\tau_v$ does vary dramatically between villages.

Thus, conditional on productivity, we will observe a remoteness gradient, simply because fertilizer is more expensive in remote areas due to travel costs. The subsidy dramatically reduces $c_v$ by about 75%, but increases $\tau_v$, because only some retailers accept FISP. Overall, however, the travel cost-adjusted price of fertilizer falls by about 50% (Table 1). Thus, the expected return will be higher for most or all farmers, and less likely to be negative for farmers with large values of $\tau_v$. Thus, we expect to observe a smaller distance gradient for subsidized fertilizer.

## 3.6 Remoteness and Coupon Redemption

Having established that travel cost-adjusted prices for subsidized (and unsubsidized) fertilizer are higher in remote areas, our next question is about the extent to which these prices translate into lower redemption of the subsidy. For each FISP beneficiary, we asked questions about coupon redemption.

In Table 2, we regress subsidy redemption on remoteness. Columns 1-2 show the extensive margin while Columns 3-4 show quantities. Odd-numbered columns do not include controls, while even-numbered columns control for the variables analyzed in Table A2. Columns 1-2 show that 95% of those receiving the subsidy redeem it. More remote farmers are less likely to redeem, but only slightly: an additional standard deviation of remoteness is associated with a decline of only 2 percentage points on the extensive margin, and 2-2.6 kg lower quantities (3.5% on a base of 70 kg, significant at 10%). As discussed later, we conjecture that the reason for the modest correlation between distance on redemption is because the ∼75% subsidy is so generous that people are willing to incur transport costs to avail of it, whereas they are less likely to do so at full market prices.

# 4 FISP and the Spatial Gradient in Fertilizer Adoption

## 4.1 Was the FISP allocation exogenous?

While FISP was purportedly randomized, it may not necessarily have been implemented as such in practice; and even if it were, it may appear non-random in our sample due to mismatch between our list of farmers and the official list used for allocation. We examine the allocation by studying how time-invariant characteristics vary between FISP beneficiaries and non-beneficiaries in Table A3. Here, we pool the 3 study years and check for covariate balance between beneficiaries and non-beneficiaries during this period.

For each characteristic, we report its sample mean in Column 1 and the coefficient from a bivariate regression of that variable on a FISP indicator in Column 2. In Column 3, we report a multivariate regression on all the variables together. We find several statistically significant coefficients, including household head age, being related to the chief, household size, land size, and receiving FISP in the prior year.

While the above results suggest that there is some amount of selection into FISP, our primary goal in this paper is not to estimate the effect of FISP itself, but to examine how FISP affects the spatial gradient in input usage. The main threat to identification is thus differential selection into FISP by proximity to market centers. To examine this, we run the following specification:

$$Y_{iv} = \alpha FISP_{ivt} + \beta R_v + \gamma FISP_{ivt} * R_v + \tau_t + \lambda_v + \varepsilon_{ivt} \tag{3}$$

In this specification, $Y_{iv}$ is a given characteristic for farmer $i$ in village $v$, $FISP_{ivt}$ is FISP beneficiary status in year $t$, and $R_v$ is remoteness (at the village level). The regression also includes year ($\tau_t$) and village ($\lambda_v$) fixed effects.

The primary coefficient here is $\gamma$, which shows how the difference in observables between FISP beneficiaries and non-beneficiaries varies with remoteness. Results are shown in Table 3. Again, while we see differences between FISP and non-FISP households on several dimensions, we find that the interaction between FISP and remoteness is statistically insignificant for all variables with the exception of receiving FISP in the prior year. In regards to that variable, prior receipt of FISP is less strongly correlated with current receipt in more remote villages; all else equal, this should work against our empirical results (to the extent that receiving FISP in a prior year predicts current usage).

## 4.2 Difference-in-difference specification

Given the issues identified in the prior subsection, we estimate effects using the following difference-in-difference framework:

$$I_{ivt} = \beta R_v + \gamma FISP_{ivt} + \delta FISP_{ivt} * R_v + \tau_t \; + \mu_i + \varepsilon_{iv} \tag{4}$$

where $I_{ivt}$ is input usage by household $i$ in village $v$ in year $t$, $R_v$ is our measure of remoteness, $FISP_{ivt}$ is an indicator for receiving FISP, and $\mu_i$ and $\tau_t$ are household and year fixed effects. Standard errors are clustered at the village level. Thus, $\beta$ shows the input adoption - remoteness gradient for non-FISP beneficiaries, and $\delta$ shows whether this gradient is attenuated for FISP beneficiaries.

To justify our empirical approach, we first run the following fixed effects placebo regression, in which we regress current input usage on FISP status in the subsequent season, as well as an interaction with FISP in the subsequent year and remoteness:

$$Y_{ivt} = \gamma FISP_{ivt+1} + \delta FISP_{ivt+1} * R_v + \mu_i \ + \tau_t + \varepsilon_{iv} \tag{5}$$

Note, however, that we can only run this specification for 2017-18 and 2018-19, because the FISP program was replaced by AIP in 2019-20, which was originally planned as a universal benefit (though in subsequent years, the program has become much less generous).

Results are shown in Table 4. Columns 1 and 3 show regressions including only the indicator for FISP in the next year, while Columns 2 and 4 include the interaction between remoteness and FISP next year. We see negative, insignificant point estimates on FISP in all specifications. The interaction is also negative and small, but significant at 10% in Column 4. Moreover, it also goes in the opposite direction as our expected result, and so if anything, it should attenuate effects.

## 4.3 Results

We present results in Table 5. In Columns 1 and 3, we show descriptive regressions without fixed effects but with household controls. As in our work in Tanzania, a context which does not subsidize fertilizer, we find that FISP non-beneficiaries' usage is decreasing in remoteness: one standard deviation of remoteness is associated with a 10 percentage point decline in the likelihood of using fertilizer, and about a 7.5 kg (12%) decline in quantities. Further, FISP is associated with a 13 percentage point increase in usage on the extensive margin and 15 kgs on the intensive margin, while the coefficient for the interaction between FISP and remoteness is 11 percentage points and 12 kg, respectively. Thus, in the cross-section, a standard deviation increase in remoteness is associated with a sizeable reduction in fertilizer use among non-beneficiaries, but there is no such gap among beneficiaries. It may surprising that in Column 3, for quantities, the sum of $\beta$ and $\gamma$ is actually positive (and significant at 5%), rather than zero (as is the case on the extensive margin in Column 1). We do not want to over-interpret these results, but do investigate this in Table A4, which shows fertilizer sharing between beneficiaries and non-beneficiaries. We find that beneficiaries in remote areas are less likely to share fertilizer with non-beneficiaries, explaining how remote farmers use more fertilizer despite redeeming (slightly) less.

Our preferred specification, however, is in Columns 2 and 4 where we include household fixed effects. For the FISP coefficient, we find some attenuation, but continue to see a statistically significant correlation between FISP receipt and input usage (of 9 percentage points on the extensive margin and 10 kgs in quantities).[20]

We now turn to our main coefficient of interest, the interaction between FISP and remoteness. Here, we find effects of 7 percentage points on the extensive margin and 10 kg in quantities, suggesting that FISP meaningfully narrows the spatial input gap.[21] Finally, we also examine our results using only the 2 seasons for which we can conduct the placebo test (2017-18 and 18-19) in Table A7, and results look qualitatively similar.

In Appendix B, we perform several robustness checks, to address issues about possible selection into the sample. In Table B1-Table B3, we redo our analysis while dropping those who received FISP in 2016-17, to (partially) address the issue that FISP is autocorrelated over time. In Table B4-Table B6, we drop those related to the chief. Even with these restrictions, results are similar to our main results.

[20]Table A5 reports randomization inference p-values. The results are qualitatively unchanged.

[21]We also check the effect of FISP on harvests for our sample, and report the results in Table A6. As with other work, which has found fertilizer use to be a noisy predictor of yields, we do not find significant effects, but they are directionally consistent with the findings in the remainder of the paper.

# 5 Conclusion

Fertilizer subsidies are widely used to increase input usage, but farmers must often incur travel costs to redeem them. What effect do these costs have on how program benefits accrue over space? We study this question in the context of Malawi's FISP, which provides a 75% subsidy on a $75 worth of inputs.

Despite meaningfully higher travel costs in remote villages, we find that redemption rates are only slightly lower in such villages. This result stands in contrast to earlier work showing how small costs discourage the adoption of a variety of products, such as preventive health (Dupas and Miguel 2017), index insurance (Cole et al. 2013), and electricity (Lee et al. 2020). A likely explanation for the difference in our results is that subsidized fertilizer is so valued as a product that relatively smaller travel costs are not a major deterrent.

Our main contribution is to examine how the subsidy affects usage among more remote farmers. We document a statistically significant and economically meaningful negative relationship between remoteness and input usage. However, we find that this gradient is attenuated among FISP beneficiaries, meaning that FISP lowers the remoteness penalty in input adoption.

Thus, we show that beyond increasing average input usage, the subsidy plays an important role in reducing spatial disparities, and can complement policies such as reducing transportation costs via infrastructure improvements. This additional benefit afforded by subsidies should be explored further in future work on subsidy design. Nevertheless, even with nearly universal redemption, welfare benefits of the subsidy are still smaller in remote areas, since remote farmers must travel further to redeem and thus pay higher travel cost-adjusted prices. While these added travel costs were modest enough (relative to the benefit of the inputs) to not discourage redemption in this case, this may not be true in other contexts.

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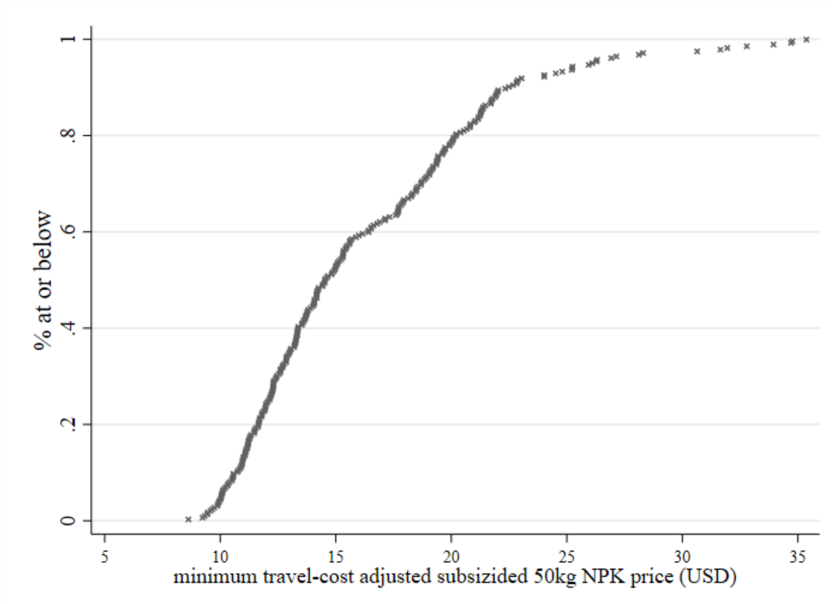
# Results

Figure 1: CDF of Travel Cost Adjusted Prices across Villages - Subsidized Fertilizer




Note: Unit of observation is the village (N = 300).

Table 1: Access to retailers, travel cost-adjusted price heterogeneity, and remoteness

| | Mean (SD) | Coefficient on remoteness measure |
|---|---|---|
| **Panel A: Summary Measures of access to input retailers** | | |
| Has atleast 1 agro-retailer within 10 kms of village which | | |
| sells fertilizers | 0.88 | -0.14*** |
| | (0.33) | (0.05) |
| sells FISP fertilizers | 0.62 | -0.11** |
| | (0.49) | (0.04) |
| Distance (in kms) to nearest agro-retailer which | | |
| sells fertilizer | 5.83 | 1.93*** |
| | (4.62) | (0.49) |
| sells FISP fertilizer | 10.14 | 3.61*** |
| | (8.76) | (0.92) |
| **Panel B1: Market Fertilizer** | | |
| Minimum travel cost adjusted price | 34.34 | 1.90*** |
| | (4.51) | (0.30) |
| ***Decomposition of price between retail price and travel costs*** | | |
| Retail price at location w. lowest travel cost adjusted price | 28.91 | 0.06** |
| | (0.56) | (0.03) |
| Cost of travel | 5.43 | 1.84*** |
| | (4.41) | (0.29) |
| **Panel B2: FISP Fertilizer** | | |
| Minimum travel cost adjusted price | 17.89 | 3.81*** |
| | (9.52) | (0.66) |
| ***Decomposition of price between retail price and travel costs*** | | |
| Retail price at location w. lowest travel cost adjusted price | 8.78 | -0.08*** |
| | (0.58) | (0.03) |
| Cost of travel | 9.11 | 3.89*** |
| | (9.39) | (0.66) |
| Observations | 300 | 300 |

Notes: Results are shown for NPK fertilizer. Regressions are at the village level. Each row represents a separate regression of the given dependent variables on standardized remoteness. Robust standard errors are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively. All costs are in USD, calculated using an exchange rate of 714 MWK to 1 USD.

Table 2: Remoteness and Coupon Redemption

| | Probability of Redemption | | Quantity redeemed (kg) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Remoteness ($\beta$) | -0.02*** | -0.02** | -2.05* | -2.61* |
| | (0.01) | (0.01) | (1.15) | (1.53) |
| Mean | 0.95 | 0.95 | 70.35 | 70.35 |
| Observations | 930 | 930 | 930 | 930 |
| Household controls | N | Y | N | Y |

Notes: Regressions are restricted to FISP beneficiaries. The dependent variable is an indicator for redeeming FISP in Columns 1-2 and the quantity redeemed in Columns 3-4. See text for definition of remoteness measure. Data is from three agricultural seasons, 2017-18 to 2019-20. All regressions include year fixed effects. Standard errors clustered at the village level are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 3: FISP Status and Remoteness

| | Mean (SD) | Coefficients on variables: FISP | FISP × Remoteness |
|---|---|---|---|
| | (1) | (2) | (3) |
| Household head age (in 10 years) | 4.37 | 0.20*** | -0.01 |
| | (1.51) | (0.06) | (0.06) |
| Related to chief | 0.48 | 0.03* | 0.01 |
| | (0.50) | (0.02) | (0.02) |
| =1 if female headed household | 0.40 | -0.01 | -0.01 |
| | (0.49) | (0.02) | (0.02) |
| Number of household members | 4.88 | 0.15* | 0.10 |
| | (2.04) | (0.08) | (0.08) |
| Education level of respondent | 4.68 | -0.13 | 0.12 |
| | (3.38) | (0.12) | (0.12) |
| FISP coupon received last year | 0.14 | 0.04*** | -0.03* |
| | (0.35) | (0.02) | (0.02) |
| Land size (acres) | 1.71 | 0.16*** | -0.01 |
| | (1.40) | (0.05) | (0.05) |
| Observations | 6,827 | | |
| Households | 2,564 | | |

Notes: Data is from three agricultural seasons, 2017-18, 2018-19 and 2019-20. Mean of FISP status is 13%. Data is restricted to households that grew maize. Each row represents a separate regression of the dependent variable on FISP status and FISP × Remoteness. Column 1 shows the mean and standard deviation of household characteristics, while Columns 2-3 show regression coefficients. All regressions include village fixed effects. Standard errors are clustered at the village level and are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 4: Placebo Check

| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Received FISP next year | -0.01 | -0.01 | -0.30 | -0.74 |
| | (0.02) | (0.02) | (2.45) | (2.47) |
| Received FISP next year × Remoteness | | -0.03 | | -3.35* |
| | | (0.02) | | (2.00) |
| Dependent variable mean | 0.80 | 0.80 | 43.75 | 43.75 |
| Observations | 4455 | 4455 | 4455 | 4455 |
| Households | 2530 | 2530 | 2530 | 2530 |

Notes: Table regresses current fertilizer usage in year $t$ on FISP allocation status in year $t+1$. Data is from two agricultural seasons, 2017-18 and 2018-19 (year $t$). All regressions include year and household fixed effects. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 5: FISP and the Input Adoption-Remoteness Gradient

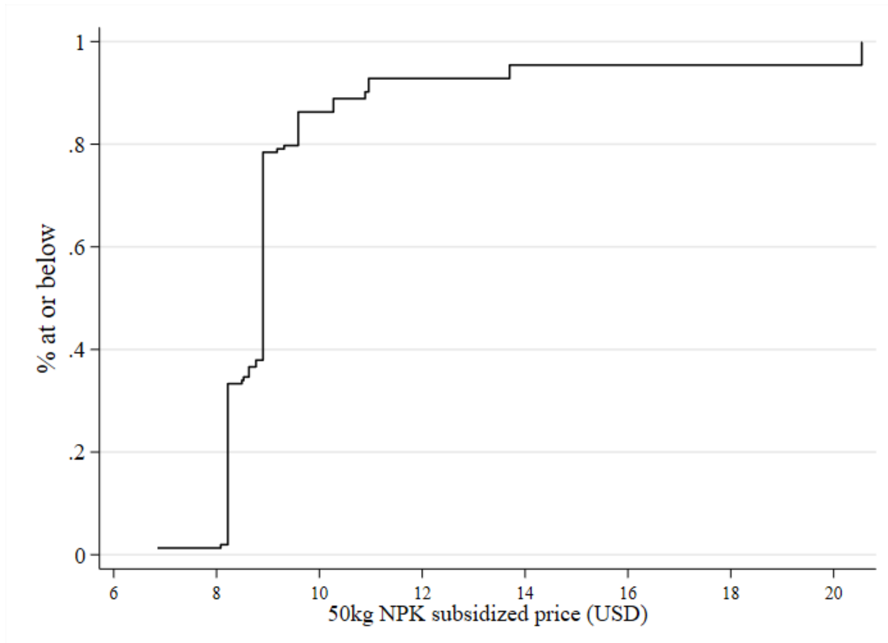
| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| FISP | 0.13*** | 0.09*** | 14.78*** | 9.56*** |
| | (0.01) | (0.01) | (1.88) | (1.95) |
| Remoteness ($\beta$) | -0.10*** | | -7.49*** | |
| | (0.01) | | (1.19) | |
| FISP $\times$ Remoteness ($\gamma$) | 0.11*** | 0.07*** | 12.14*** | 9.98*** |
| | (0.01) | (0.01) | (2.11) | (2.03) |
| *p-value*: $\beta + \gamma$ | 0.85 | | 0.04 | |
| Dependent variable mean | 0.83 | 0.83 | 53.71 | 53.71 |
| Observations | 6827 | 6827 | 6827 | 6827 |
| Households | 2564 | 2564 | 2564 | 2564 |
| Household FE | N | Y | N | Y |

Notes: Columns 1 and 3 include all the variables in Table 3, while Columns 2 and 4 include household fixed effects. Data is restricted to households that grew maize. Table includes data from three agricultural seasons, 2017-18, 2018-19 and 2019-20. Remoteness is a standardized measure at the village level. All regressions include year fixed effects. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

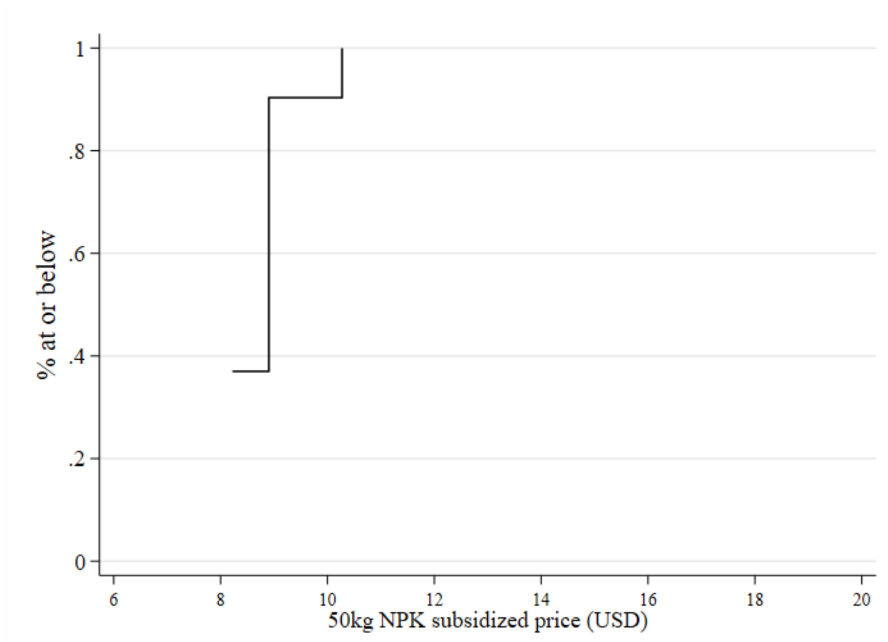
# Appendix A: Additional Results

Figure A1: CDF of Subsidized FISP Prices (Retailer level)

(a) Universe of retailers



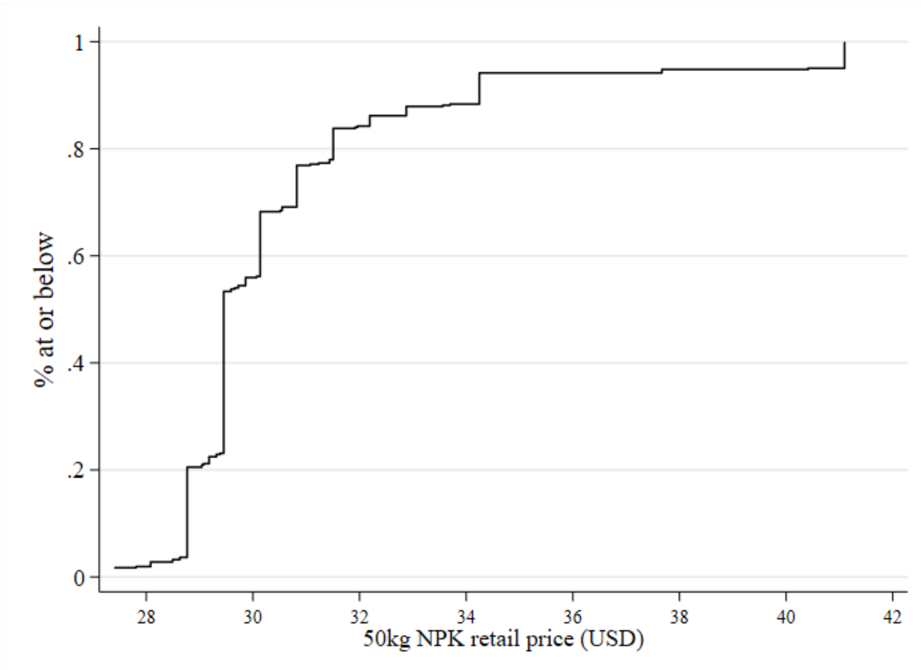

(b) Retailers Identified as Lowest Cost option



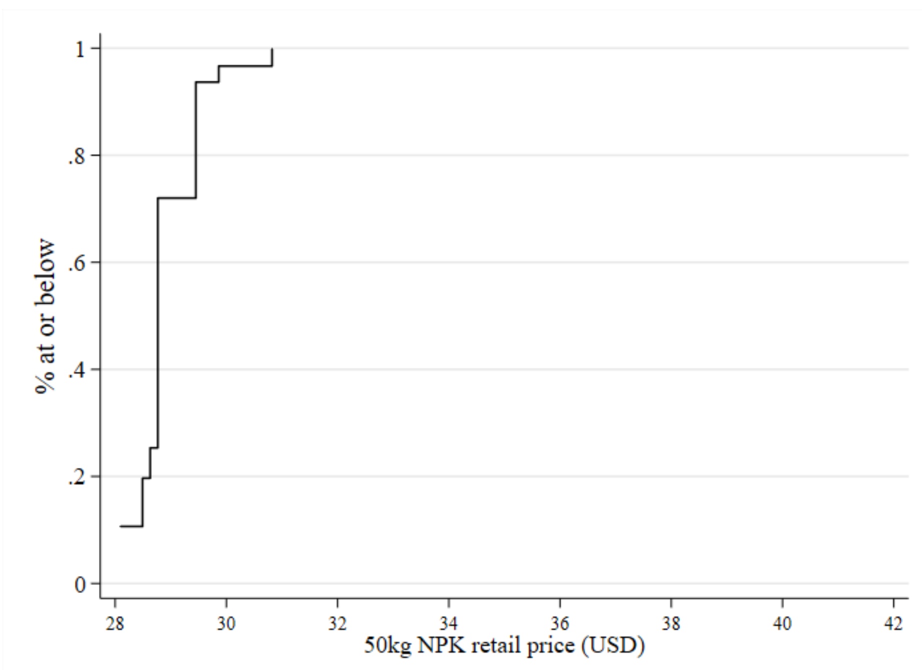

Note: Figure presents the CDF of the travel cost-adjusted price for subsidized FISP fertilizer. Unit of observation is the retailer. Panel A shows the distribution across all the retailers in the sample (N=153), while Panel B shows the distribution across only those retailers chosen by our algorithm as the lowest cost option (N=12).

Figure A2: CDF of Retail Prices (Retailer level)

(a) Universe of retailers




(b) Retailers identified as lowest cost option




Note: Figure presents the CDF of the travel cost-adjusted price for retail fertilizer. Panel A shows the distribution across all the retailers in the sample (N=463), while Panel B shows the distribution across only those retailers chosen by our algorithm as the lowest cost option (N=20).

Table A1: Agro-input Dealer Summary Statistics

| | (1) Mean | (2) SD |
|---|---|---|
| Number of years in business | 6.15 | 5.64 |
| =1 if selected for FISP in past 2 years | 0.47 | |
| *At the time of survey:* | | |
| =1 if sells NPK | 0.97 | |
| =1 if sells Urea | 0.95 | |
| =1 if sells CAN | 0.43 | |
| =1 if sells DAP | 0.09 | |
| *In last year (2018):* | | |
| Number of 50kg bags of NPK sold | 858.41 | 1,561.76 |
| Number of 50kg bags of Urea sold | 692.81 | 1,256.80 |
| Number of 50kg bags of CAN sold | 101.07 | 248.17 |
| Number of 50kg bags of DAP sold | 0.00 | 0.00 |
| Total revenue from selling fertilizer last year (USD) | 32,728.74 | 71,519.06 |
| Observations | 466 | |

Note: Sample restricted to shops that sell any NPK or Urea. Variables winsorized at 95th percentile.

Table A2: Correlation between Remoteness and Farmer Characteristics

| | Mean (SD) | Remoteness |
|---|---|---|
| | (1) | (2) |
| **Panel A: Farmer Characteristics** | | |
| =1 if female headed household | 0.40 | -0.04 |
| | (0.49) | (0.03) |
| Household head age (in 10 years) | 4.38 | -0.10 |
| | (1.52) | (0.26) |
| Related to Chief | 0.48 | 0.07** |
| | (0.50) | (0.03) |
| Household size | 4.89 | 0.36 |
| | (2.03) | (0.30) |
| Respondent years of education | 4.72 | -0.75*** |
| | (3.37) | (0.29) |
| FISP coupon received last year | 0.16 | -0.03** |
| | (0.36) | (0.01) |
| Land size in acres | 1.70 | 0.11 |
| | (1.40) | (0.11) |
| **Panel B: Production Capacity (in kg/acre)**[1] | | |
| FAO-GAEZ production capacity for low input level | 2.37 | 0.45*** |
| | (0.93) | (0.15) |
| FAO-GAEZ production capacity for high input level | 8.48 | 1.42*** |
| | (2.71) | (0.54) |
| Observations | 2367 | 2367 |

Data is restricted to households that grew maize in 2017-18. Standard Errors clustered at village level are in parentheses. Estimates include regression of dependent variables in column 1 on remoteness measures. FAO variables have been rescaled by dividing by 1000.

[1]Regressions for production capacity are at village level.

Table A3: Comparing FISP Beneficiaries and Non-Beneficiaries

| | Mean/(SD) | Bivariate | Multivariate |
|---|---|---|---|
| | (1) | (2) | (3) |
| Household head age (in 10 years) | 4.37 | 0.011*** | 0.010*** |
| | (1.51) | (0.003) | (0.004) |
| Related to chief | 0.48 | 0.019* | 0.018* |
| | (0.50) | (0.011) | (0.010) |
| =1 if female headed household | 0.40 | -0.005 | -0.002 |
| | (0.49) | (0.010) | (0.010) |
| Household size | 4.89 | 0.004* | 0.003 |
| | (2.04) | (0.002) | (0.002) |
| Education level of respondent | 4.67 | -0.002 | 0.001 |
| | (3.36) | (0.001) | (0.002) |
| FISP coupon received last year | 0.14 | 0.047*** | 0.044*** |
| | (0.35) | (0.016) | (0.016) |
| Land size in acres | 1.71 | 0.010*** | 0.007** |
| | (1.40) | (0.004) | (0.004) |
| $p$-value for F-test on joint significance | | | 0.00 |
| Observations | 6,827 | 6,827 | 6,827 |
| Households | | 2,564 | 2,564 |

Notes: Data is from three agricultural season, 2017-18, 2018-19 and 2019-20. Data is restricted to households that grew maize. The dependent variable takes value as 1 if the household received FISP. Dependent variable mean is 13%. Column 1 shows the control mean and standard deviation, column 2 shows coefficients of a bivariate regression of FISP status on household characteristics and includes village fixed effects and column 3 shows coefficients of a multivariate regression of FISP on household characteristics and village fixed effects. Standard errors are clustered at the village level and are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table A4: Remoteness and Sharing / Selling of FISP Benefits

| | Quantity received by non-coupon holders (kg) | | Quantity shared or sold by coupon holders (kg) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Remoteness ($\beta$) | -9.13*** | -8.12*** | -7.65*** | -7.82*** |
| | (0.78) | (0.91) | (1.08) | (1.25) |
| Household controls | N | Y | N | Y |
| Mean | 27.67 | | 27.17 | |
| Observations | 6153 | 6153 | 923 | 923 |

Notes: Regressions are restricted to non-coupon holders in columns 1 and 2, and FISP coupon holders in columns 3 and 4. All coefficients are from separate regressions of the respective dependent variable on remoteness measure. The dependent variable in Columns 1-2 is the quantity of FISP fertilizer bought by non-beneficiaries. On average, 46 kgs were sold by farmers for a total of $0.05. Data is from one agricultural seasons, 2017-18. Remoteness is a standardized measure at the village level. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table A5: Randomization Inference p-values

| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| FISP | 0.13*** | 0.09*** | 14.78*** | 9.56*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Remoteness ($\beta$) | -0.10*** | | -7.49*** | |
| | (0.00) | | (0.00) | |
| FISP x Remoteness ($\gamma$) | 0.11*** | 0.07*** | 12.14*** | 9.98*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Dependent variable mean | 0.83 | 0.83 | 53.71 | 53.71 |
| Observations | 6827 | 6827 | 6827 | 6827 |

Notes: All regressions include household controls. Household controls include variables in Table 3. Columns (2) and (4) also include household fixed effects. Data is restricted to households that grew maize. Remoteness is a standardized measure at the village level. Randomization inference p-values are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table A6: FISP, Remoteness and Harvest Quantity

| | (1) | (2) |
|---|---|---|
| FISP | 23.78* | 22.13 |
| | (13.26) | (16.53) |
| Remoteness ($\beta$) | -46.13*** | |
| | (7.84) | |
| FISP $\times$ Remoteness ($\gamma$) | 31.78** | 17.05 |
| | (13.42) | (16.84) |
| *p-value*: $\beta + \gamma$ | 0.28 | |
| Dependent variable mean | 411.13 | 411.13 |
| Observations | 6328 | 6328 |
| Households | 2520 | 2520 |
| Household FE | N | Y |

Notes: Column (1) includes household controls. Household controls include variables in Table 3. Columns (2) also includes village fixed effects. Data is restricted to households that grew maize. Data is from three agricultural seasons, 2017-18, 2018-19 and 2019-20. The dependent variable winsorized at 95th percentile. Remoteness is a standardized measure at the village level. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table A7: FISP and the Input Adoption-Remoteness Gradient, for 2017-18 and 2018-19 only

| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| FISP | 0.16*** | 0.06*** | 16.16*** | 6.77*** |
| | (0.01) | (0.01) | (2.10) | (2.14) |
| Remoteness ($\beta$) | -0.12*** | | -9.94*** | |
| | (0.01) | | (1.43) | |
| FISP $\times$ Remoteness ($\gamma$) | 0.13*** | 0.03** | 13.16*** | 12.29*** |
| | (0.01) | (0.02) | (2.27) | (2.33) |
| *p-value*: $\beta + \gamma$ | 0.55 | | 0.18 | |
| Dependent variable mean | 0.80 | 0.80 | 43.01 | 43.01 |
| Observations | 4455 | 4455 | 4455 | 4455 |
| Households | 2530 | 2530 | 2530 | 2530 |
| Village FE | N | Y | N | Y |
| Household FE | N | Y | N | Y |

NNotes: Columns 1 and 3 include all the variables in Table 3, while Columns 2 and 4 include household fixed effects. Data is restricted to households that grew maize. Table includes data from two agricultural seasons, 2017-18 and 2018-19. Remoteness is a standardized measure at the village level. All regressions include year fixed effects. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

# Appendix B: Robustness

## Robustness to excluding households that received FISP in 2016-17

Table B1: Determinants of FISP Beneficiary Status, excluding households who received FISP in 2016-17

| | | Coefficients on variables: | |
|---|---|---|---|
| | Mean (SD) | FISP | FISP × Remoteness |
| | (1) | (2) | (3) |
| Household head age (in 10 years) | 4.33 | 0.20*** | 0.01 |
| | (1.52) | (0.06) | (0.06) |
| Related to chief | 0.48 | 0.04** | 0.00 |
| | (0.50) | (0.02) | (0.02) |
| =1 if female headed household | 0.40 | -0.02 | -0.03 |
| | (0.49) | (0.02) | (0.02) |
| Number of household members | 4.88 | 0.20** | 0.07 |
| | (2.04) | (0.08) | (0.08) |
| Education level of respondent | 4.68 | -0.11 | 0.12 |
| | (3.38) | (0.13) | (0.14) |
| Land size (acres) | 1.70 | 0.13** | 0.01 |
| | (1.39) | (0.06) | (0.05) |
| Observations | 5,856 | | |
| Households | 2,515 | | |

Notes: Data is from three agricultural seasons, 2017-18, 2018-19 and 2019-20. Mean of dependent variable is 13%. Data is restricted to households that grew maize. Each row represents a separate regression of the dependent variable on on FISP status and FISP × Remoteness. Column 1 shows the mean and standard deviation of household characteristics, while Columns 2-3 show regression coefficients. All regressions include village fixed effects. Standard errors are clustered at the village level and are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table B2: FISP and the Input Adoption-Remoteness Gradient, excluding households who received FISP in 2016-17

| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| FISP | 0.13*** | 0.08*** | 14.06*** | 11.68*** |
| | (0.01) | (0.02) | (1.99) | (2.26) |
| Remoteness ($\beta$) | -0.11*** | | -7.11*** | |
| | (0.01) | | (1.24) | |
| FISP $\times$ Remoteness ($\gamma$) | 0.11*** | 0.07*** | 11.07*** | 9.28*** |
| | (0.01) | (0.02) | (2.05) | (2.44) |
| *p-value*: $\beta + \gamma$ | 0.78 | | 0.06 | |
| Dependent variable mean | 0.82 | 0.82 | 52.26 | 52.26 |
| Observations | 5856 | 5856 | 5856 | 5856 |
| Households | 2515 | 2515 | 2515 | 2515 |
| Household FE | N | Y | N | Y |

Notes: Columns 1 and 3 include all the variables in Table 3, while Columns 2 and 4 include household fixed effects. Data is restricted to households that grew maize. Table includes data from three agricultural seasons, 2017-18, 2018-19 and 2019-20. Remoteness is a standardized measure at the village level. All regressions include year fixed effects. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table B3: Placebo Check, excluding households who received FISP in 2016-17

| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Received FISP next year | -0.05* | -0.05* | 2.61 | 2.41 |
| | (0.03) | (0.03) | (3.39) | (3.34) |
| Received FISP next year × Remoteness | | -0.02 | | -3.83 |
| | | (0.02) | | (2.38) |
| Dependent variable mean | 0.79 | 0.79 | 43.13 | 42.54 |
| Observations | 3867 | 3867 | 3817 | 3867 |
| Households | 2410 | 2410 | 2391 | 2410 |

Notes: This table regresses FISP allocation status in the next (t+1) year on outcomes in the current (t) year. All regressions include household controls. Household controls include variables in Table 3. All regressions include year fixed effects. Data is restricted to households that grew maize. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

## Robustness to excluding households that are related to the chief

Table B4: Determinants of FISP Beneficiary Status, excluding household related to chief

| | Mean (SD) | Coefficients on variables: FISP | Coefficients on variables: FISP × Remoteness |
|---|---|---|---|
| | (1) | (2) | (3) |
| Household head age (in 10 years) | 4.36 | 0.16* | -0.07 |
| | (1.50) | (0.08) | (0.10) |
| =1 if female headed household | 0.38 | -0.04* | -0.02 |
| | (0.485) | (0.02) | (0.03) |
| Number of household members | 4.88 | 0.21* | 0.31** |
| | (2.034) | (0.12) | (0.13) |
| Education level of respondent | 4.93 | 0.21 | 0.24 |
| | (3.444) | (0.18) | (0.18) |
| FISP coupon received last year | 0.14 | 0.01 | -0.06** |
| | (0.343) | (0.02) | (0.03) |
| Land size (acres) | 1.68 | 0.12 | 0.01 |
| | (1.41) | (0.08) | (0.07) |
| Observations | 3,533 | | |
| Households | 1,337 | | |

Notes: Data is from three agricultural seasons, 2017-18, 2018-19 and 2019-20. Mean of dependent variable is 13%. Data is restricted to households that grew maize. Each row represents a separate regression of the dependent variable on on FISP status and FISP × Remoteness. Column 1 shows the mean and standard deviation of household characteristics, while Columns 2-3 show regression coefficients. All regressions include village fixed effects. Standard errors are clustered at the village level and are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table B5: FISP and the Input Adoption-Remoteness Gradient, excluding household related to chief

| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| FISP | 0.14*** | 0.10*** | 16.63*** | 10.75*** |
| | (0.01) | (0.02) | (2.83) | (3.08) |
| Remoteness ($\beta$) | -0.11*** | | -6.80*** | |
| | (0.02) | | (1.52) | |
| FISP $\times$ Remoteness ($\gamma$) | 0.11*** | 0.08*** | 14.85*** | 10.88*** |
| | (0.02) | (0.02) | (3.53) | (2.99) |
| *p-value*: $\beta + \gamma$ | 0.88 | | 0.03 | |
| Dependent variable mean | 0.84 | 0.84 | 54.82 | 54.82 |
| Observations | 3533 | 3533 | 3533 | 3533 |
| Households | 1337 | 1337 | 1337 | 1337 |
| Household FE | N | Y | N | Y |

Notes: Columns 1 and 3 include all the variables in Table 3, while Columns 2 and 4 include household fixed effects. Data is restricted to households that grew maize. Table includes data from three agricultural seasons, 2017-18, 2018-19 and 2019-20. Remoteness is a standardized measure at the village level. All regressions include year fixed effects. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table B6: Placebo Check, excluding household related to chief

| | =1 if used fertilizer | | KGs of fertilizer used | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Received FISP next year | -0.01 | -0.01 | -0.36 | -1.00 |
| | (0.02) | (0.02) | (3.79) | (3.83) |
| Received FISP next year × Remoteness | | -0.01 | | -2.25 |
| | | (0.03) | | (2.96) |
| Dependent variable mean | 0.81 | 0.81 | 45.18 | 44.35 |
| Observations | 2301 | 2301 | 2259 | 2301 |
| Households | 1314 | 1314 | 1300 | 1314 |

Notes: This table regresses FISP allocation status in the next (t+1) year on outcomes in the current (t) year. All regressions include household controls. Household controls include variables in Table 3. All regressions include year fixed effects. Data is restricted to households that grew maize. Standard errors clustered by village are in parentheses. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

# Appendix C: Technical Appendix

In section 3.2, we estimate trade costs using a multinomial logit motivated by a spatial model to recover the ad-valorem trade costs implied by farmer decision-making. An outline of the model, estimation and results is below.

Precisely, suppose that a farmer $f$ from village $i$ chooses from a set of agro-retailers $j \in J$ that are located in a set of villages $v \in V$. The retail price charged at an agroretailer $j$ in $v$ is $r_{vj}$. Buying from each agroretailer involves receiving a productivity shock with a mean that is specific to the agroretailer, and distributed Frechet. Following Aggarwal et al. (2024a), the farmer, on each trip in our dataset, chooses among available agro-dealer locations, incurring an ad-valorem trade cost $\tau_{iv}$ in traveling from their village $i$ to agro-dealer-location $v$. Using this modeling structure, it is straightforward to derive that the probability a farmer $f$ from village $i$ chooses some agro-dealer from village $v$ on trip $t$ (t's suppressed for brevity) is the following.

$$\Pr\left(v \ chosen\right) = \frac{\exp\left(\delta_v - \varepsilon \log(\tau_{iv})\right)}{\sum_{v'}\sum_{j'} \exp\left(\delta_{v'} - \varepsilon \log(\tau_{iv'})\right)} \tag{6}$$

Here, $\delta_v$ captures the quality adjusted retail prices of retailers in location $v$, which farmers weight against the trade costs in traveling from their village $i$ to the agro-dealer location $v$. Given the structure of our data, we adopt a simple specification for trade costs, where the elasticity-adjusted ad-valorem cost is a linear function of distance on main roads, $Main_{iv}$, and the distance on rural roads, $Rural_{iv}$. Thus, the specification we take to the data can be written as:

$$\Pr\left(j \ in \ v \ chosen\right) = \frac{\exp\left(\delta_v + \alpha Main_{iv} + \beta Rural_{iv}\right)}{\sum_{v'}\sum_{j'} \exp\left(\delta_{v'} + \alpha Main_{iv} + \beta Rural_{iv}\right)} \tag{7}$$

Equation (7) can be estimated by McFadden's alternative-specific conditional logit. As explained in the text of the manuscript, we use our novel "trips" module to construct our dataset, where for each trip in our sample, the farmer chooses among $V$ agrovet-villages to travel from/to village $i$. The results from estimating the model using this dataset are presented in Appendix Table C1. Column 1, which is the baseline model for the paper, uses a sample of agrovet trips for farmers who did not receive FISP coupons, and also trips for a sample of farmers who received a FISP coupon but did not use it on these trips. Column 2 only uses a sample of farmers who did not receive FISP coupons. Clearly, in both columns, distance on main roads has a smaller effect on agro-dealer-location-choice than distance on rural roads, which implies higher trade costs for rural roads.

To quantify these estimates in a way that is informative, we need to link the semi-elasticities of agrovet choice to distance (the estimates) to actual costs of travel. This requires a utility parameter $\varepsilon_a$, the elasticity of substitution across agrovets, which (ideally) can be estimated using random variation in retail prices, or calibrated to an existing market equilibrium using demand and supply conditions. We can do neither in our paper since retail prices are not random across locations and we do not have a representative sample of consumer demand and supply in the entire geographic area. So, we instead appeal to our earlier work in Aggarwal et al. (2024a), where we construct a geographically representative sample of farmer demand for fertilizer and agrovet supply in northern Tanzania. In spatial equilibrium, we find that $\varepsilon_a \approx 8$ is consistent with that equilibrium. This is about twice as large as the existing average estimates of gravity elasticities of movement, and is intuitive larger since rural farmers in poor areas are likely to be more price sensitive than firms in global trade.[22]

Using $\varepsilon_a \approx 8$, we can calculate the ad-valorem equivalent trade cost for any length of trip with any main-rural composition of travel. For example, the average trip in our data includes 2.55 km on main roads and 6.62 on rural roads. Using these distances, and $\varepsilon_a = 8$, we calculate that the ad-valorem equivalent trade cost for the average trip is 24%. At the mean retail price of \$30, this trade cost is approximately \$7.48 - a substantial sum for farmers

[22] Monte et al. (2018) finds that the elasticity of commuting to distance is 4.43.

in this region.

Table C1: Estimates from Multinomial Logit Model

| | (1) | (2) |
|---|---|---|
| KM on Main Roads | -0.163*** | -0.163*** |
| | (0.0081) | (0.0083) |
| KM on Rural Roads | -0.201*** | -0.199*** |
| | (0.0086) | (0.0089) |
| Observations | 370,760 | 344,816 |

**Notes:** Column 1, which is the baseline model for the paper, uses a sample of agrovet trips for farmers who did not receive FISP coupons, and also trips for a sample of farmers who received a FISP coupon but did not use it on these trips. Column 2 only uses a sample of farmers who did not receive FISP coupons. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$