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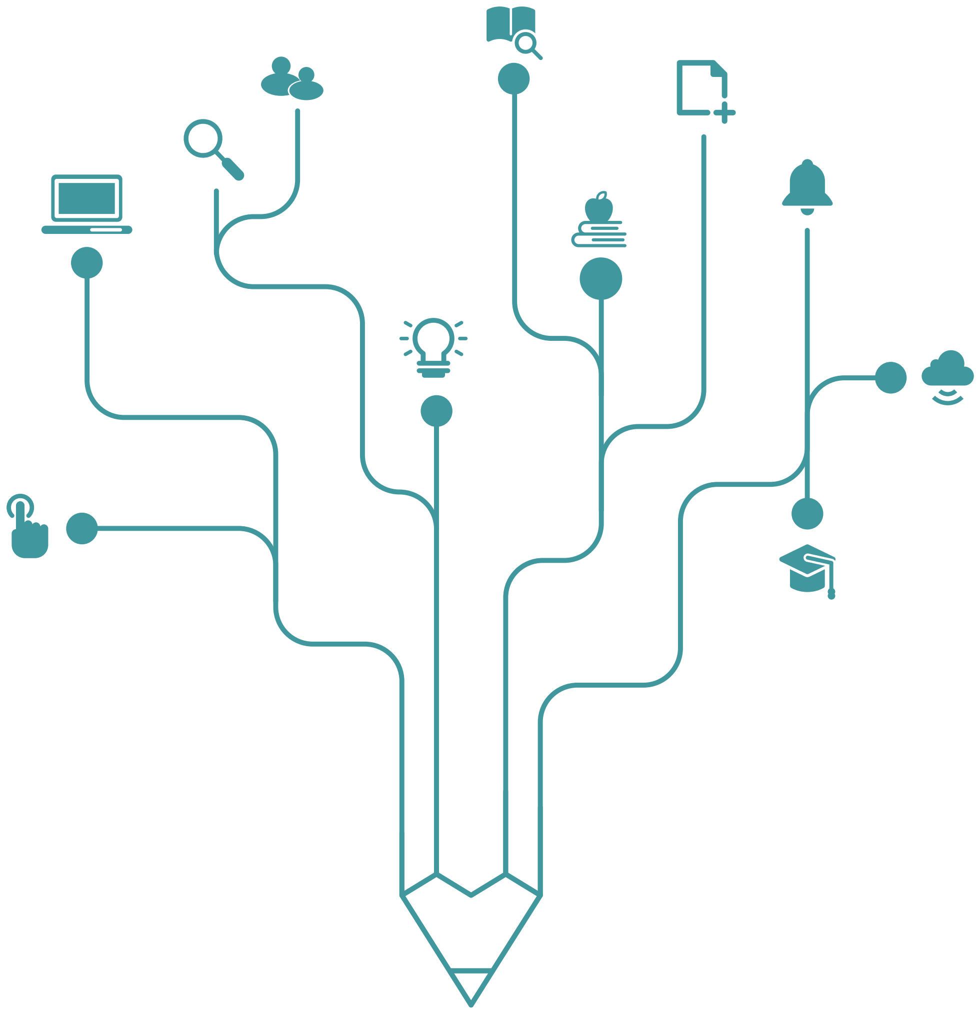

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Abstract

Many countries subsidize agricultural inputs but require farmers to travel to retailers to access inputs, 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 show that travel-cost-adjusted prices are substantially higher in remote areas. However, subsidy redemption is nearly universal. We make use of a policy change in 2017-19 which took centralized control of beneficiary selection and find that FISP eliminates the sizeable remoteness gradient that exists for non-beneficiaries. Our results demonstrate that subsidy programs may narrow spatial inequities.

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

Keywords: input subsidies, technology adoption, transport costs, FISP

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1 Introduction

Poor transportation infrastructure impedes access to input markets (World Bank 2008; World Bank 2017), lowering input usage and agricultural productivity in remote areas (Aggarwal et al. 2022; Minten et al. 2013; Shamdasani 2021). To reduce these spatial inequalities, much of the policy and research discussion has been on the role of 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 used across the developing world to spur agricultural productivity generally,[1] they are usually aimed at improving the general level of input usage, and not necessarily designed for mitigating spatial gradients.

A priori, input subsidies should generate spatial convergence, since less remote farmers are more likely to already be using inputs. However, in practice, many subsidy programs still 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 receive coupons that must be redeemed at selected fertilizer retailers; thus, remote farmers must still incur transport costs to travel to distant input retailers. It is therefore possible that a subsidy program could leave the distance gradient unchanged or may even worsen it if subsidy take-up is sufficiently elastic to travel costs. Quantifying the effect of distance is thus, an important question with implications for the design of subsidy programs.

In this paper, we study spatial differences in FISP prices, redemption, and input usage by households using survey data of 2,664 maize farmers in 300 villages in 2 districts of Southern Malawi, as well as surveys of the universe of agricultural input dealers in the area. FISP provides a subsidy worth about 75% of the retail cost of $75 worth of chemical fertilizer and seeds, i.e., a subsidy worth about $56, a substantial sum for our sample in which we measure

[1] At least 10 countries in this region of Africa have large-scale subsidy programs, representing the largest outlay of their respective agricultural budgets (Dorward et al. 2004; Jayne et al. 2018).

average monthly expenditure of a household to be just over $30. During the time period of our study (2017 and 2018), the subsidy was disbursed in the form of a paper coupon, which had to be presented for redemption at selected participating local retailers.[2] Though the program has been scaled down over time, it is still large, reaching just under 15% of farming households in our data.

We follow our prior work in Tanzania (Aggarwal et al. 2022) to construct a measure of market access for fertilizer by calculating the travel cost-adjusted price farmers face. We collected prices of fertilizer for the universe of agricultural input dealers in the region, and use Google Maps API to calculate distances from each of the 300 villages in our sample to every retailer. To estimate travel costs, we estimate 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, and find the minimum such price a farmer faces. For both subsidized and unsubsidized fertilizer, we find that travel costs are substantial, on average about $5.6 for market fertilizer and $9.2 for subsidized fertilizer (the larger value for subsidized fertilizer is because only certain retailers are selected to participate in the program, so farmers have to travel farther on average to reach them.). Because the subsidy reduces the retail price by 75%, the implied ad-valorem travel cost is sizeable for unsubsidized fertilizer (about 20%) but enormous for subsidized fertilizer (over 100%).

We find that a 1 standard deviation increase in remoteness is associated with a $1.9 increase in the travel-cost-adjusted prices of unsubsidized fertilizer (about 6%), and a $3.8 increase in the price of subsidized fertilizer (about 21%). Essentially all of this gradient is driven by travel costs, as retail prices are nearly identical across the various locations in our sample (the standard deviation in retail prices is only about $0.56, less than 2% of the mean price of $29).

[2]Typically, larger chains were selected to participate in the program.

What effect do these higher prices have on redemption? Somewhat surprisingly, we find only a modest effect of remoteness on subsidy redemption: a one standard deviation increase in remoteness is associated with a reduction in the probability of redemption of only about 2 percentage points (on a base of 95%) and is associated with a reduction in the quantity of fertilizer redeemed by 3.6 kgs (on a base of 61 kg).

This result strongly implies that receiving the FISP subsidy should largely eliminate the gradient in fertilizer usage. To examine this causally, we utilize a policy change in which beneficiary selection in FISP moved away from local leaders to a centralized selection process that was meant to be random. Historically, FISP had been officially targeted towards disadvantaged farmers and beneficiary selection was largely delegated to local chiefs. However, there was also evidence of elite capture and nepotism, due to which, in 2017, the government of Malawi transitioned from identifying beneficiaries via local leaders to one in which beneficiaries were selected by officials in the Ministry of Agriculture, purportedly randomly. We examine this policy for the 2017-18 and 2018-19 planting seasons.[3]

To examine whether the allocation is truly exogenous and not affected by household characteristics, we regress FISP receipt on key background characteristics that predicted usage in prior years. We find no significant correlation between observable demographic characteristics and FISP receipt, but do observe that having received FISP in the year before the rule change (2016-17) predicts receiving it during the treatment period (2017-18 and 2018-19). This correlation might be because the listing of households may be incomplete (so that those already on the listing are more likely to receive it than the average household), or could possibly be due to some mismeasured preference for certain households (we do see positive coefficients on variables measuring relationship to the chief, though not significant in our sample). Given these results, we take the exogeneity of the program as questionable, and we include controls for these variables in our results.

[3]We exclude 2019-20 because in our data we find that many respondents reported receiving partial coupons, which is not consistent with program rules. We conjecture that the program may have been affected by external factors, such as the disputed Presidential election in 2019-20.

As in our prior work in Tanzania, we examine the correlation between remoteness and input usage, but differentiate between beneficiaries and non-beneficiaries. Among non-beneficiaries, we find a statistically significant gradient in input usage: 1 standard deviation of remoteness is associated with about a 13 percentage point decline in input usage on the extensive margin, and 29% in quantities. FISP, however, mitigates this gap: in fact, we cannot reject that FISP completely eliminates the gradient.[4] While this is to be expected from the above results – because there is no gradient in subsidized fertilizer usage, and because the subsidy is large enough to cover the average farmer's entire land – the result speaks to the (often overlooked) role that subsidies can play in equalizing access gradients.

Our paper adds to the literature about agricultural subsidies, including recent randomized evaluations such as Carter et al. (2013), Carter et al. (2021), Fishman et al. (2022) and Gignoux et al. (2023). In doing so, we corroborate the findings from much of this literature that the subsidy had a large effect on contemporaneous use,[5] though our focus is on extending this literature to look at the heterogenous effect of subsidy by remoteness. Within this literature, we contribute to the substantial workstream about FISP specifically, which also finds large productivity benefits of the subsidy, but is from a period that pre-dates the centralization of the program.[6] By utilizing the centralized allocation, we corroborate the findings from this set of papers in a convincingly causal framework. As a group, these studies show that subsidies can be effective even in contexts with high baseline fertilizer use, such as Malawi.

Our paper is also related to a large and growing literature about the effect of market access on agricultural input adoption (Porteous 2019, Gebresilasse 2023, Aggarwal et al.

[4]However, remote farmers are still disadvantaged to more proximate farmers – because they still must travel further to access the subsidy and pay substantially higher prices once travel costs are properly accounted for.

[5]The findings in Gignoux et al. (2023) are an exception, in that they find that an input subsidy in Haiti actually *decreased* input usage among beneficiaries, a phenomenon that the authors attribute not to the subsidy itself but to misinformation about continued subsidy receipt which crowded-out private input usage.

[6]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), and Basurto et al. (2020)

2023b, Dillon and Tomaselli 2022), although much of this work has focused on interventions that directly reduce transport costs but leave the prices of the inputs themselves largely unchanged, such as those that build roads or organize input fairs close to rural villages (in their local markets). This paper, on the other hand, studies the interplay between market access and technology adoption in the context of heavily subsidized inputs. In doing so, we also contribute to earlier work on the costs of accessing subsidies, which documents the large effect of small co-pays on the 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 travel costs rather than on retail costs.

2 Background and Data

2.1 Institutional Context

Malawi has a unimodal rainfall pattern with a single rainy season which runs from approximately November to April/May.[7] Since 2004, the Malawian Ministry of Agriculture has provided agricultural input subsidies via the Farm Input Subsidy Program (FISP). While FISP reached as much as two-thirds of farming households in earlier years, in more recent years the program has been scaled back: in data we collected starting in 2014, only about 15% of households received the subsidy in a given year.

Traditionally, local leaders had authority over the selection of beneficiaries. 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 random beneficiary selection by district officials using a centralized list of eligible farmers, which is updated every year.

During the time period that we study (2017-18 and 2018-19), FISP included subsidies for 4 inputs - 50 kg each of NPK and Urea fertilizer, 5 kg of hybrid maize seeds,[8] and 2 kg

[7] See FEWSNET for the crop calendar for a typical year.

[8] Farmers could also choose to use this voucher for 7 kg of open-pollinated variety maize or sorghum

of hybrid legume seeds. The full package is sufficient for using the recommended amounts of inputs to cultivate a 1 acre plot of land. The market value of this package was about $75 during the years of study, and the FISP subsidy was worth 75% of the market cost, meaning that a beneficiary would have to pay approximately $18 for the full package.

Farmers receive these coupons as a single leaf with 4 separate detachable coupons, one for each input, and farmers can redeem as many or as few of these coupons as they wish. However, each individual coupon must be redeemed in its entirety, i.e., it is not possible to redeem a coupon for less than the full quantity (which is likely one reason why there is widespread sharing of subsidized inputs). Because the subsidy is generous, take-up is nearly universal. In our data covering the 2017 and 2018 agricultural seasons, we find that 95% of beneficiaries redeemed their coupons.

Because of the longstanding nature of FISP, Malawi has a well-developed input retail sector with a high density of shops. For example, in our sample, nearly 90% of the villages had an agro-retailer within a 10 km radius, while in our companion work in Tanzania, a far more developed country, this number was only 62%. On the other hand, road connectivity in the country is at par for the region - Malawi has 130 km of road per 1000 sq km of area, of which about a quarter is paved, which mimics the averages for sub-Saharan Africa as a whole, although it is better than Tanzania (92 km and 13% respectively).

2.2 Data

For our analysis, we use surveys of households and agricultural input dealers that were collected for an evaluation of unconditional cash transfers in 300 villages in Chiradzulu and Machinga districts in the Southern Region of Malawi.[9] First, to construct an analysis sample of households, we randomly selected 10 households per village in each of the 300 villages for surveys, successfully completing baseline surveys with 2,944 households in April-July 2019, out of which we drop 464 farmers because either they do not own land (one of

seeds.

[9]See Aggarwal et al. (2023a) for more details.

the criteria for being listed) or do not grow maize (the focus crop for FISP). Thus our final sample for this analysis is 2480 farmers (i.e., 84% of the baseline sample). In the baseline survey, we collected information on the 2017-18 and 2018-19 planting seasons.[10] Our surveys collected standard demographic data, as well as information about FISP receipt, redemption, and subsidy sharing, as well as asked detailed questions on ultimate input usage (from all sources) and yields. To precisely measure market access, we also included questions on the location and cost of purchasing inputs (including travel costs).

Second, we conducted a census of agriculture 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. We identified a total of 466 retailers that sold fertilizer in the census, 431 of which completed the longer survey (92%).

The census occurred in 2 waves: March 2019 in our study districts, and 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). For the 35 agro-dealers that could not be surveyed later, we use the prices reported in the census. Once this database was constructed, we examined it for outliers and found that 8 retailers clearly had data errors (1.7% of the sample), and had prices far from the mean (likely due to missing zeroes or because of unit conversion mistakes). We rely on the law of one price within markets to correct these as 7 out of these 8 were located in markets with at least one other agro-dealer.[12]

[10]The endline survey for the project included information on the 2019-20 season, but we do not use this data because program implementation may have been compromised during the disputed Presidential election of 2019; we find that households report being coupon recipients at a rate that is nearly 3 times that in 2017 and 2018 (even though there were no changes in the official FISP policy) and many respondents reported receiving partial coupons.

[11]We included these neighboring districts to be able to accurately calculate price dispersion within our study region, since farmers near district borders may travel across them to access inputs.

[12]In our data, we find that the law of one price holds within locations for which we have data on multiple agro-dealers: the standard deviation of the price within a location is only 10% of the mean.

We show some summary statistics about the agro-dealers in Table A1. The average agro-dealer has been in business for 6 years and about half the agro-dealers are authorized to sell under FISP. The average operation is fairly large, having earned nearly $33,000 in revenue in the previous year, which is more than 50 times the per capita income of Malawi; however, there is a lot of heterogeneity in size. Agro-delaers almost universally sell NPK and Urea, and sell large amounts of both.

3 Defining Market Access and Remoteness

Our analysis is closely related to our prior work in Tanzania (Aggarwal et al. 2022), which examined correlations between remoteness, market access, and input usage. This paper extends that work to exploit exogenous variation in the subsidy (and hence input usage). We use many of the same variable definitions and regression specifications as in that prior work. In this section, we briefly describe these concepts (and refer the reader to our prior paper for a more extended discussion, as well as alternative robustness checks).

3.1 Defining market access

Similar to Donaldson and Hornbeck (2016), we define market access in terms of distance to local population centers. Specifically, we focus on 3 major markets: Blantyre, Lilongwe, and Zomba, the three biggest cities in the country, of which Blantyre and Zomba are the closest regional market towns for the sample of villages in our study (the median distance to Zomba is 44.4 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 τ_{hv} from surveys in which we asked about the cost of travel to purchase fertilizer.[13] For $-\theta$, we appeal to the substitution elasticity across agro-retailers which is estimated in Tanzania to be -7.9. 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). Since Google Maps API information is not reliable within villages, market access is indexed at the village-level v, rather than by farmer.

As would be expected, more remote villages differ from more proximate villages in 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 have fewer years of education, are less likely to own a business and are poorer (as evidenced by having a thatch roof). However, these correlations do not impact our primary regression specifications. We have two main sets of results: descriptively documenting market access across villages, and causally identifying the impact of FISP (which is randomized *within* village). Nevertheless, for robustness, we include the full set of controls shown in this table in our main specifications (causing only modest changes in coefficients).

3.2 Agrodealer choice and estimating travel costs

In Aggarwal et al. (2022), we estimate travel costs via two methods: a calibration method that includes only pecuniary costs, and a method that estimates a structural choice model to account for all pecuniary and non-pecuniary costs (such as the risk of stock-outs requiring multiple trips, lack of information about options in distant locations, the valuation of own time, and related issues). We find that total costs are about 4-5 times higher than pecuniary costs in Tanzania, and we find that model-estimated costs and behavior match observable moments quite well. In this paper, we, therefore, rely solely on model-estimated costs.

As mentioned in Section 2.2, our surveys with agro-dealers give us the universe of prices in

[13] Farmers must make a round-trip, and the return trip is more costly since the farmer is carrying the fertilizer with her. In surveys, we estimate that the cost of transporting a bag is about 40% of that of a person; therefore a farmer effectively incurs 2.4 times the one-way travel costs.

the area. We then use Google Maps API to estimate driving times and distances from every village in our sample to every identified agricultural input dealer. In our survey, we asked respondents about every instance in which they purchased inputs, the name and location of the relevant input 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).

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. For the trade costs, we assume that the ad-valorem rate is a function of distance traveled on different road types (i.e. main roads and rural roads).[14] Further technical details are relegated to Appendix B.

To measure baseline trade costs without including any wealth implications of receiving FISP, we use a sample of farmers who did not receive FISP. The results from the estimation (presented in Appendix Table B1) 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 1 km increase in rural road travel increases costs by 2.6% (i.e. the marginal effect of rural road travel is about 45% greater). To calculate a dollar value of estimated trade costs, we use the retail price and apply the estimated coefficients to recover the unit-value of trade costs.

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:

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

[14] In Malawi, road names are based on pavement classification, which are "M" (main roads, primarily paved), "S" (secondary, often unpaved) and "T" (tertiary, unpaved local feeder roads). Google API includes this information.

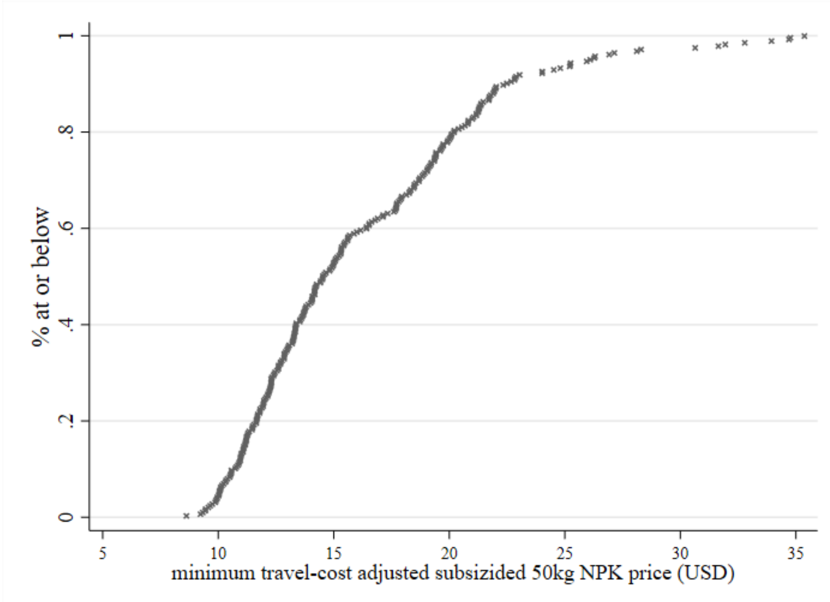
where r_j is the price at agro-retailer j and c_{vj} is the cost of traveling to agro-retailer j, and returning to village v with a bag of fertilizer.

Figure A1 plots distributions of prices which show how the decision rule affects calculated price dispersion. First, Panel A shows the unconditional distribution of subsidized FISP prices at all of the 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 the decision rule (2), we find that only 12 total retailers are chosen. Eight of these are located within the study districts (out of 65 total in the 2 districts), and 4 are located outside (all in the hub locations 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.[15]

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 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).

[15] For reference, Figure A2 shows a similar figure for the *retail* price. Here in Panel A, we find an unconditional mean and sd 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 is \$28.9 and \$0.5.

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



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

3.4 The relationship between remoteness and market access

Table 2 shows the relationship between remoteness and various measures of access to NPK fertilizer, the most widely available input in the country, along with urea.[16] First, in Panel A we show some summary measures of access to retailers. We find that 88% of villages have at least 1 input retailer within 10 km. Access is superior to that documented in our prior work in Tanzania (Aggarwal et al. (2022)), where only about 60% of villages were within 10 km of a retailer. However, since only a subset of retailers participate in FISP, we find that only 62% of the villages have at least 1 retailer accepting FISP. The average distance to the nearest retailer is 5.8 km for market fertilizer, and 10.1 km for FISP.

Despite a deeper overall market, we still observe a large remoteness penalty. A standard deviation increase in the remoteness measures leads to a 14 pp decline in the likelihood of having an agrodealer within 10 km of the village (11 pp for one that accepts FISP). The distance to the nearest agro-retailer also increases substantially, with every standard-deviation of remoteness adding between about 1.9 km (mean 5.8 km) for market fertilizer

[16] We show results only for NPK here. Those for Urea are very similar and available upon request.

and 3.6 km (mean 10.1 km) for FISP fertilizer, i.e., about a 33% increase for either "type" of fertilizer.

Table 1: Remoteness and price heterogeneity for subsidized and market NPK fertilizer

	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: Each cell represents a separate regression. Estimates include regression of dependent variables in column 1 on remoteness measures. 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.

We then turn to analyzing prices in Panels B1 (for market fertilizer) and B2 (for FISP fertilizer). For both subsidized and unsubsidized fertilizer, 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 (at the same agro-dealer). For market fertilizer, we find the average minimum price to be $34.3, with a standard deviation of \$4.5. In the decomposition, we see that \$29 of this is the retail price, with a small SD of only \$0.5. To this, another \$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.[17]

For FISP fertilizer, we find that while farmers pay about 75% less on the retail price, they incur roughly \$9 in trade costs on average (about 64% more than for retail fertilizer, due to the fact that only some retailers accept coupons). 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 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 (and mute its adoption benefits). For each FISP beneficiary, we asked whether the coupon was redeemed and, if so, for what quantity. In Table 2, we regress subsidy redemption on remoteness, on the extensive margin (Columns 1-2) and on quantities (Columns 3-4). Odd-numbered columns show regressions without controls, while even-numbered columns include all the variables analyzed in Table A2 as covariates. We also include household controls, which we describe later in Table 3.

[17] Note that despite its input market depth, Malawi has much higher fertilizer prices 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.

Table 2: Remoteness and Coupon Redemption

	Probability of Redemption		Quantity redeemed (kg)	
	(1)	(2)	(3)	(4)
Remoteness	-0.01*	-0.02*	-3.38**	-3.56**
	(0.01)	(0.01)	(1.50)	(1.51)
Mean	0.95	0.95	61.30	61.30
Observations	710	710	710	710
Household controls	N	Y	N	N

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 pooled for two agricultural seasons, 2017-18 and 2018-19. 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.

Columns 1-2 show that redemption is nearly universal to begin with: 95% of those who receive 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 1-2 percentage points on the extensive margin (significant at only 10%). Columns 3-4 show evidence of modestly lower quantities redeemed in remote areas: an additional standard deviation is associated with about 3.4-3.6 kg lower quantities (about 5% on a base of 60 kg). While this coefficient is significant at 5%, it is still a relatively small quantity, and therefore, has limited economic significance. As discussed in more detail later, we conjecture that the reason for the modest effect of distance on redemption is because the $\sim$75% subsidy is so generous that people are willing to incur the transport costs, whereas they are less likely to do so at full market prices.

4 Utilizing the change in FISP rules

4.1 Was the FISP allocation random?

As discussed above, official government policy traditionally targeted FISP towards certain groups, such as older or resource-poor farmers, and in practice, chiefs had at least some amount of discretion over distribution within their village, so that the literature has documented evidence of manipulation by the chiefs (Basurto et al. (2020). While FISP was purportedly randomized during the study period, it may not necessarily have been implemented as such in practice. To evaluate this, we check for balance between FISP beneficiaries and non-beneficiaries in Table 3. In the Table, Column 1 reports the mean while Column 2 presents coefficients from a regression of FISP on a set of predetermined characteristics, pooling both the seasons in which FISP was randomized (2017-18 and 2018-19). All regressions include village fixed effects (discussed in more detail below).

We check balance on all time-invariant characteristics that we collect in our survey, which are unlikely to have been impacted by prior receipt of FISP, including the respondent's relationship to the chief, household size, household head's age, gender and years of education, and land size. In addition, we also check for correlations with a indicator for whether the respondent had received FISP in 2016, the year prior to randomization. Of all these characteristics, we find that receiving FISP in 2016 is the only significant predictor of receiving it even after the program was centralized. Our conjecture is that this effect may be driven by some households potentially being missing in the household listing, such that those already on the list are more likely to receive it than the average household. It is also possible that there may be some preference for certain kinds of households.

Finally, as mentioned earlier, these regressions all include village fixed effects. While FISP was random even across villages, it is possible that targeting across villages is more subject to violations of randomization than within villages. For example, the listing of households by different enumerators and district offices could vary across villages. In Table A3 we show the same regressions without village fixed effects. While the pattern of coefficients is very similar, several are now significant (namely household age, gender of the head and being related to the chief). The coefficients are still fairly small but for this reason, we prefer to use village fixed effects in all the specifications that follow.

Table 3: Determinants of FISP Beneficiary Status

	Mean	Coefficients from multivariate regression
	(1)	(2)
Household head age (in 10 years)	4.43	0.006
	(1.53)	(0.004)
=1 if chief's spouse or child	0.05	0.031
	(0.22)	(0.030)
=1 if other relative of chief	0.45	0.021
	(0.50)	(0.013)
=1 if female headed household	0.40	-0.017
	(0.49)	(0.011)
Household size	4.92	0.002
	(2.04)	(0.003)
Respondent years of education	4.69	0.000
	(3.37)	(0.002)
Acres under maize cultivation	1.70	0.006
	(1.37)	(0.004)
Received FISP in 2016-17	0.14	0.042**
	(0.35)	(0.019)
Mean of Dependent Variable	0.14	
Households	2,480	2,480
Observations	4,960	4,960

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

4.2 The effect of FISP on the remoteness gradient

Given the results on subsidy redemption, we should expect FISP to mitigate spatial differences in input usage. To formally establish this, as well as to quantify the gradient in input adoption that exists for non-beneficiaries, we run the following regression:

$$Y_{ivt} = \beta R_v + \gamma FISP_{ivt} + \delta FISP_{ivt} * R_v + \gamma X_{iv} + \mu_v + \phi_t \ + \ \varepsilon_{ivt} \tag{3}$$

where Y_{ivt} is the relevant variable for input usage by household i in village v in year t, R_v is one of our 2 (standardized) measures of remoteness, $FISP_{ivt}$ is an indicator for receiving FISP, X_{iv} are time-invariant household-level controls, μ_v is a vector of village fixed effects and ϕ_t is that of year fixed effects. Standard errors are clustered at the village level. In this specification, γ shows the input adoption - remoteness gradient for non-FISP beneficiaries, and δ shows how this gradient is attenuated for FISP beneficiaries. Results are shown in Table 4. In the table, we first present results without village fixed effects μ_v (in Columns 1 and 3). While the specification without village fixed effects is less robust than the one with (as shown previously), we present this in order to show the remoteness coefficient (note that we also include a full set of controls X_{iv}). We then present the more robust specification with village fixed effects in Columns 2 and 4.

First, as expected, we find a large, statistically significant effect of FISP. Receiving FISP increases the probability of usage by about 12-16 percentage points (on a base of 80%), and 14-16 kgs (on a base of 45 kg). These effects are in the same ballpark as those in Carter et al. 2021 which show about a 16 pp. effect on the extensive margin and a 17 kg one on the intensive margin, albeit on a much smaller base than in our context. Results are slightly attenuated with the inclusion of village fixed effects, but still highly significant.

Second, as in our work in Tanzania, we find that FISP non-beneficiaries' usage is decreasing in remoteness: one standard deviation of remoteness is associated with a 13 percentage point decline in the likelihood of using fertilizer, and about a 10 kg decline in input quantities. These differences are substantial but relatively smaller than in Tanzania, where we find a similar point estimate of about 6-14 kg per SD, but where the baseline usage is much lower at only 19 kg.

Table 4: FISP and the Input Adoption-Remoteness Gradient

	=1 if used fertilizer		KGs of fertilizer used	
	(1)	(2)	(3)	(4)
FISP	0.16***	0.12***	14.84***	13.43***
	(0.01)	(0.01)	(1.91)	(1.89)
Remoteness (β)	-0.13***		-10.72***	
	(0.01)		(1.12)	
FISP $\times$ Remoteness (γ)	0.12***	0.08***	13.62***	12.37***
	(0.01)	(0.01)	(2.02)	(2.04)
p-value: $\beta + \gamma$	0.43		0.14	
Dependent variable mean	0.80	0.80	44.92	44.92
Observations	4960	4960	4960	4960

Notes: All regressions include year-fixed effects and household controls. Household controls include variables in Table A3. Columns (2) and (4) also include village fixed effects. Data is pooled for two agricultural seasons, 2017-18 and 2018-19. 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.

With this result in hand, we should expect to find that FISP reduces the effect of remoteness on input adoption. This is because coupon redemption is nearly universal, the subsidy is for a large quantity (more than baseline input usage), and because redemption is only marginally lower in remote areas; thus, it should follow that the gradient in usage among FISP beneficiaries is smaller.

Indeed, this is what we find. The interaction between FISP and remoteness is positive and significant, and similar in size to the remoteness coefficient for non-beneficiaries. In our preferred specification in Columns 2 and 4, the interaction is very similar. In the odd-numbered columns, we report a p-value for the test that the sum of coefficients is zero and cannot reject the null. In fact, if anything, we find that the farmers in remote areas use a little bit more fertilizer than their proximate counterparts conditional on using FISP (the β and γ coefficients add up to about 3 kg and are borderline significant at 14%).[18] Ultimately,

[18]It is somewhat surprising that these farmers use *more* fertilizer since we show earlier in Table 3 that

then, we find that FISP completely eliminates the gradient in input usage, indicating that the subsidy equalizes usage geographically.

5 Conclusion

Fertilizer subsidies are one of the most common policy tools to increase input usage, but farmers must often redeem their subsidies at existing retailers, incurring travel costs in the process. What effect do these travel costs have on how the benefits of these programs accrue over space? We study this question in the context of Malawi's generous Farm Input Subsidy Program, which provides a 75% subsidy on about $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 some contrast to earlier work showing how small costs discourage the adoption of a variety of products, largely in the context of preventive health (i.e. see the review in Dupas and Miguel 2017), as well as some from financial products (Cole et al. 2013). The most likely explanation for the difference in our results is that, in the case of subsidized fertilizer, the product is so valued that relatively smaller travel costs are not a major deterrent. Additionally, fertilizer has market value and could potentially be shared or sold if necessary.

Our main contribution is to examine how the subsidy affects usage among more remote farmers. Although Malawi has a more developed agro-input retailer network than other countries (such as in our prior work in Tanzania), we still document a statistically significant and economically meaningful correlation between remoteness and input usage. This correlation is entirely absent among FISP beneficiaries - because redemption is so high (and only marginally lower in remote villages), usage among beneficiaries is nearly universal, irrespective of location. Thus, we show that in addition to increasing average input usage, the

remote farmers redeem about 3-4 fewer kg of fertilizer. We investigate this is in Table A4, which shows how fertilizer is shared 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 are able to use more fertilizer despite redeeming less.

FISP subsidy plays an important role in reducing spatial disparities, and can complement other policies such as reducing transportation costs via infrastructure improvements.[19] This additional benefit afforded by subsidies should be explored further in future work on the design of subsidy programs. Nevertheless, even with nearly universal redemption, the welfare benefit of the subsidy is 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 will not necessarily be true in other contexts.

[19] In related work analyzing a road construction program, Aggarwal (2021) shows that roads improve the uptake of subsidized health facilities in rural India.

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Appendix A: Additional Results

Table A1: Agroinput 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

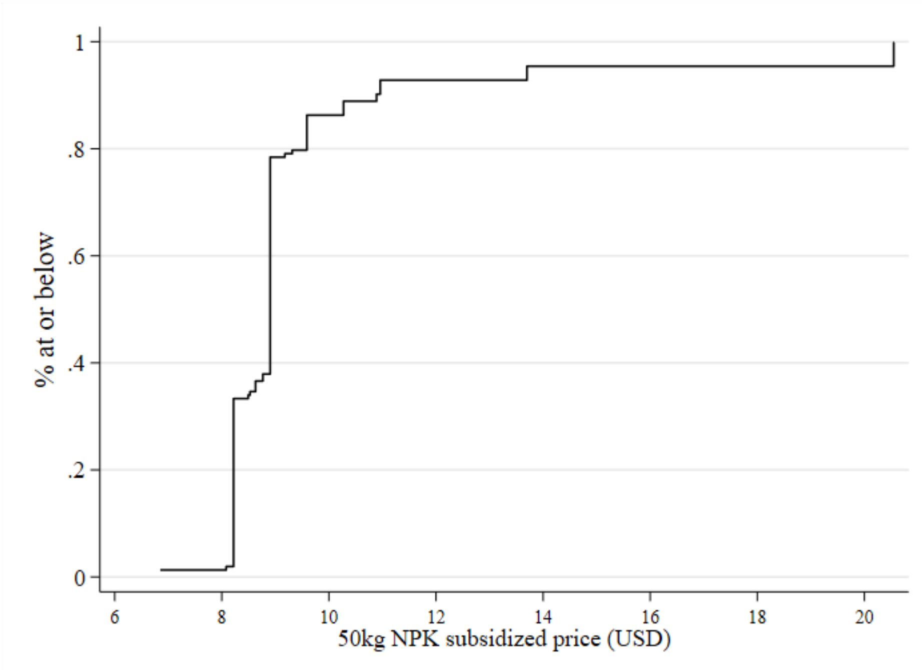
	Mean (SD)	Remoteness
	(1)	(2)
Panel A: Farmer Characteristics		
Female	0.95	0.00
	(0.23)	(0.06)
Household head age (in 10 yrs)	4.33	-0.13
	(1.55)	(0.25)
Married	0.67	0.04
	(0.47)	(0.04)
Education level of respondent	4.68	-0.74***
	(3.36)	(0.28)
Number of household members	4.91	0.38
	(2.00)	(0.30)
Owns house	0.87	0.01
	(0.33)	(0.05)
Thatch roof	0.49	0.12***
	(0.50)	(0.03)
Respondent owns a mobile phone	0.31	-0.01
	(0.46)	(0.02)
Land size in acres	1.71	0.12
	(1.37)	(0.11)
Used mobile money in last year	0.04	-0.01
	(0.19)	(0.00)
Respondent owns a business	0.22	-0.05***
	(0.42)	(0.02)
Income from business in last 30 days	2.17	-0.24
	(8.97)	(0.22)
Panel B: Production Capacity (in kg/acre)[1]		
FAO-GAEZ production capacity for low input level	2.37	0.46***
	(0.93)	(0.15)
FAO-GAEZ production capacity for high input level	8.47	1.43***
	(2.71)	(0.53)
Observations	2480	2480

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.

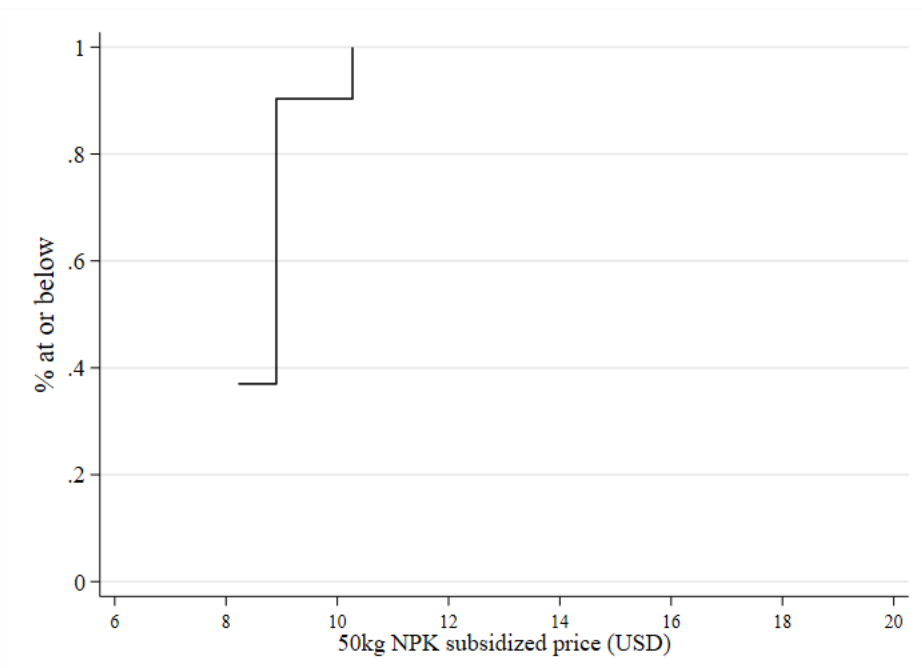
[1]Regressions for production capacity are at village level.

Figure A1: CDF of Subsidized FISP Prices at Agdealers

(a) CDF across universe of retailers



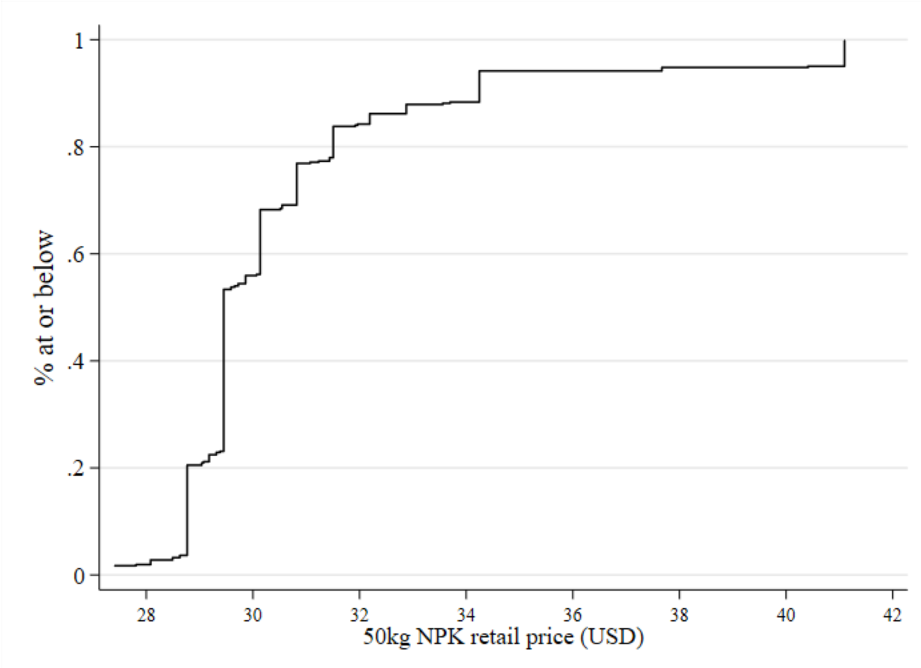
(b) CDF across retailers identified as lowest cost option



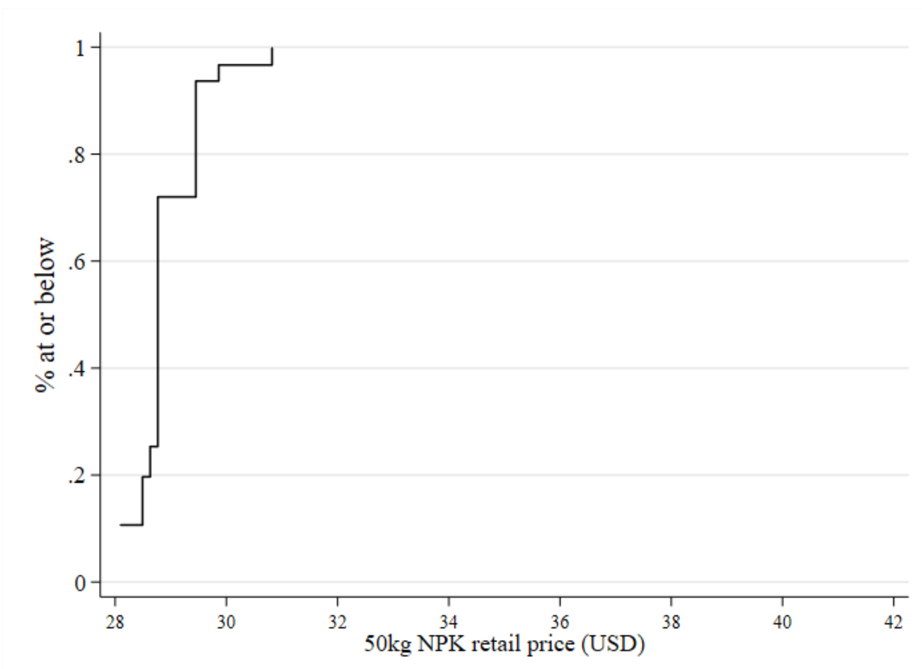
Note: Figure presents the CDF of the travel cost-adjusted price for subsidzed FISP fertilizer. Panel A shows the distribution across all the retailers in the sample (N=153), while Panel B shows the distribution across only those retailers chosen by our algorithm as the lowest cost option (N=12).

Figure A2: CDF of Retail Prices at Agdealers

(a) CDF across universe of retailers



(b) CDF across 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 A3: FISP Randomization Check (without Village Fixed Effects)

	Mean	Coefficients from multivariate regression
	(1)	(2)
Household head age (in 10 years)	4.43	0.015***
	(1.532)	(0.004)
=1 if chief's spouse or child	0.05	0.032
	(0.221)	(0.027)
=1 if other relative of chief	0.45	0.022*
	(0.498)	(0.011)
=1 if female headed household	0.40	-0.018*
	(0.490)	(0.011)
Household size	4.92	-0.001
	(2.039)	(0.003)
Respondent years of education	4.69	0.005***
	(3.372)	(0.002)
Acres under maize cultivation	1.70	0.001
	(1.366)	(0.004)
Received FISP in 2016-17	0.14	0.091***
	(0.345)	(0.018)
Households	2,480	2,480
Observations	4,960	4,960

Notes: Data pooled for two agricultural seasons, 2017-18 and 2018-19. Data restricted to households that grew maize. The dependent variable takes value as 1 if the household received FISP. The mean of the dependent variable is 0.14. Column 1 shows the control mean and standard deviation, while column 2 shows coefficients of a multivariate regression of FISP status on household characteristics and includes 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

	Quantity received by non-coupon holders (kg)		Quantity shared by coupon holders (kg)		Quantity used on own farm by coupon holders (kg)	
	(1)	(2)	(3)	(4)	(5)	(6)
Remoteness	-9.78***	-9.76***	-10.87***	-10.98***	7.49***	7.43***
	(0.84)	(0.84)	(1.39)	(1.42)	(1.33)	(1.31)
Household controls	N	Y	N	Y	N	Y
Mean	20.58		14.30		47.00	
Observations	4250	4250	710	710	710	710

Notes: Regressions are restricted to non-coupon holders in columns 1 and 2, and FISP coupon holders in columns 3-6. 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. Data pooled for two agricultural seasons, 2017-18 and 2018-19. All regressions include year fixed effects. 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.

Appendix B: 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. (2022), the farmer, on each trip in our dataset, chooses amongst available agrovet locations, incuring an ad-valorem trade cost τ_{iv} in traveling from their village i to agrovet-location v. Using this modeling structure, it is straightforward to derive that the probability a farmer f from village i chooses an agrovet from village v on trip t is the following.

$$\Pr\left(v\ chosen\right) = \frac{\exp\left(\delta_v - \varepsilon \log(\tau_{iv})\right)}{\sum_{v'}\sum_{j'} \exp\left(\delta_{v'} - \varepsilon \log(\tau_{iv'})\right)} \tag{4}$$

Here, δ_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 agrovet 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:

$$\Pr\left(j\ in\ v\ chosen\right) = \frac{\exp\left(\delta_v + \alpha Main_{iv} + \beta Rural_{iv}\right)}{\sum_{v'}\sum_{j'} \exp\left(\delta_{v'} + \alpha Main_{iv'} + \beta Rural_{iv'}\right)} \tag{5}$$

Equation (5) can be estimated by McFadden's alternative-specific conditional logit. The results from doing so are presented in Appendix Table B1. Clearly, distance on main roads has a smaller effect on agrovet-location-choice than distance on rural roads, which implies higher trade costs for rural roads.

To quantify these estimates, we appeal to Aggarwal et al. (2022) and assume $\varepsilon_a \approx 8$. In doing this, 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 costs is approximately $7.48 - a substantial sum for farmers in this region.

Table B1: Estimates from Multinomial Logit Model

	(1)
KM on Main Roads	-0.163***
	(0.0081)
KM on Rural Roads	-0.201***
	(0.0086)
Observations	370,760

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1