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

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Abstract

We evaluate a unique policy experiment in which the Government of Malawi randomized beneficiary selection for its Farm Input Subsidy Program. These subsidies can only be redeemed at local retailers, making travel cost-adjusted prices higher for remote farmers. Despite these costs, redemption is only marginally lower in remote areas. The subsidy eliminates the substantial remoteness-input quantity gradient that would exist in its absence. The equalizing effect on village-level input usage is modest because remote farmers are less likely to share subsidized inputs with non-beneficiaries. Our results demonstrate that subsidy programs may narrow spatial inequities in developing countries.

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

Keywords: input subsidies, technology adoption, transport costs, co-pays, 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 of many developing countries (Aggarwal et al. 2022b; 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 2022). In this paper, we examine the spatial properties of the impact of another policy instrument: input subsidies. While input subsidies are commonly used across the developing world to spur agricultural productivity,[1] they are typically thought of as intending to improve the general *level* of input usage and are not necessarily aimed towards mitigating spatial gradients.

A priori, we would expect input subsidies to lower dispersion in input usage, since less remote farmers are more likely to already be using inputs, making much of the impact of the subsidy on them infra-marginal. However, most subsidy programs still require beneficiaries to procure inputs at retail or specialized locations that may be located far away. In the context of Malawi, coupons are redeemed at the same input retailers that sell market fertilizer, and so remote farmers must still travel to distant input retailers, incurring significant transport costs. These costs can be large, and prior research has shown that even small costs of accessing subsidies can dramatically lower usage – e.g., previous research on bednets (Cohen and Dupas 2010) and index insurance (Cole et al. 2013). If this is the case then a subsidy program could leave the distance gradient unchanged or may even worsen it if the adoption effects are larger for the proximate non-users than for remote non-users. Quantifying the effect of distance is therefore an important question with implications for the design of subsidy programs.

In this paper, we make use of a unique policy experiment to study this question: the

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

randomization of Malawi's large-scale Farm Input Subsidy Program (FISP). 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 in a sample in which we measure average monthly expenditure of a household to be just over $30. This program is massive, amounting to about 3% of the Malawian GDP and reaching about a fifth of the country's farming households every year. In 2017, the government of Malawi transitioned from identifying beneficiaries via local leaders to one in which beneficiaries were selected randomly. Following this change, beneficiaries received discount coupons, which were then presented for redemption at local retailers.

Thus, beneficiaries of the subsidy ultimately incur the same transport cost as would be incurred in making market purchases. These transport costs are substantial: while the average subsidized price for a 50 kg bag of NPK fertilizer is $6 with a standard deviation of only $0.12 (the low variance is due to the strong retail network in Malawi), the average transport cost to the nearest agro-retailer is $3 with a standard deviation of nearly $2.[2] In this paper, we explore whether this transport cost is a deterrent to take-up of the subsidy for more remote farmers.

To do this in a rigorous causal framework, we begin by analyzing whether the allocation of FISP is consistent with random assignment. A large prior literature had documented that FISP traditionally had been targeted towards older and resource-poor farmers, and that the allocation of subsidies was largely controlled by the local chief, who targeted inputs towards relatives as well as those with higher land productivity (see the discussion in papers such as Basurto et al. 2020). However, in the years we study, we should observe no such correlations as subsidy allocation was purportedly random and decided at the district level with no involvement of the village chief. However, when we examine subsidy receipt, we see evidence of non-random targeting: we find that farmers who received FISP the prior year were more likely to receive the coupon, as were the chief, his/her spouse, and his/her children. We

[2]In related work in Tanzania, Aggarwal et al. (2022b) find that the average retail price of a 50 kg bag of fertilizer is about $20 with a standard deviation of $2.55, and the average transport cost to the nearest agro-dealer is $4.6 with a standard deviation of $5.

therefore remove these households from the analysis (about 22% of the sample). Once we do this, we find little correlation between subsidy receipt and background characteristics (the one exception is the household head's age, where we find a modest correlation; we control for this and other time-invariant household characteristics in regressions).

Next we examine the effect of FISP on current season input usage. While input usage is already high in Malawi, we find that the subsidy has a substantial effect: the probability of using any type of fertilizer increases by about 13 percentage points (base 79%), and the total quantity of fertilizer increases by roughly 30%. We find that about half of the quantity purchased from FISP crowds out purchases of market fertilizer. We also confirm the prior literature that there is widespread sharing of subsidized inputs. This sharing spillover tends to lower the first stage, but does not undo the effect of the subsidy.

The main focus of our analysis, however, is on how subsidy redemption and input adoption varies with remoteness. We construct measures of remoteness using the method discussed in Kapoor et al. (2022), which is similar to prior work in Aggarwal et al. (2022b), and which we describe in detail later in this paper. Using various measures of remoteness, we find that an additional standard deviation of remoteness is associated with a \$1.2-\$1.9 increase in travel costs. While this is not a large amount in absolute terms, it equates to an ad-valorem cost of roughly 20-30%.

We find that more remote farmers are indeed less likely to redeem their coupons, but that the gradient is relatively small: a one standard deviation increase in remoteness reduces the redemption probability by about 2 percentage points (on a base of 94%) and reduces the amount of fertilizer redeemed by 5 kgs (on a base of 75 kg). Interestingly, we find that even this small gradient in redemption does not translate into a gradient in actual on-farm *usage*, because we find that more remote farmers share less fertilizer with others (and that the reduced sharing actually fully offsets the reduction in redemption). However, these results do imply that the amount of subsidized fertilizer used in aggregate in more remote villages is less than that used in proximate villages (i.e. non-beneficiaries benefit less from sharing spillovers) – though the effect is not massive (i.e. about 5/75=7%).

Finally, we examine the implications of the subsidy for the remoteness gradient in ultimate input usage. While we find a significant remoteness gradient among non-beneficiaries, we cannot reject that the gradient is completely eliminated among beneficiaries. 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 is related to several strands of the literature. First, it adds to a literature about agricultural subsidies, including recent randomized evaluations such as Carter et al. (2013), Carter et al. (2021), Fishman et al. (2021) and Gignoux et al. (forthcoming) as well as a substantial literature about FISP specifically.[3] In doing so, we corroborate the findings from much of this literature that the subsidy had a large effect on contemporaneous use,[4] and we also show that the FISP context seems to be differentiated from others by its large take-up.

Second, the paper is related to a large and growing literature about the effect of market access, particularly in regards to agricultural input adoption (Minten et al. 2013, Gebresilasse 2022). Our work is also related conceptually to studies examining the effect of travel costs on usage of public services such as hospitals, many of which tend to be heavily subsidized in developing countries (Aggarwal 2021, Adhvaryu and Nyshadham 2015, Abu-Qarn and Lichtman-Sadot 2022).

Third, our work is related to earlier work documenting the effect of small co-pays on take-up of products such as bednets, chlorine, or deworming pills (i.e. Cohen and Dupas 2010, Ashraf et al. 2010, Kremer and Miguel 2007). In our context, we find that travel

[3]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). These studies all pre-date the randomization of the program.

[4]The findings in Gignoux et al. (forthcoming) are an exception, in that they find that the subsidy actually *decreased* input usage among beneficiaries, a phenomenon that the authors attribute not to the subsidy itself but to misinformation about continued subsidy receipt.

costs are not a substantial deterrent, presumably because the perceived value of fertilizer is high enough that people are willing to incur the cost. Indeed, in our sample, the usage rate of fertilizer for the control group is 79%, suggesting that the benefits of fertilizer are well-understood in this context.

2 Institutional Context

Malawi has a unimodal rainfall pattern with a single rainy season,[5] for which planting occurs around November and harvest occurs around April-May. Since 2004, the Malawian Ministry of Agriculture has provided agricultural input subsidies via the Farm Input Subsidy Program (FISP), which has become one of the largest agricultural subsidy programs in the developing world. 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 15-20% of households received the subsidy in a given year.

Traditionally, local leaders, in particular village chiefs, had authority over the identification and selection of beneficiaries. However, this system was criticized as being inefficient and subject to elite capture.[6] In response, in 2017 the Ministry of Agriculture implemented a program where Ministry of Agriculture officials themselves select beneficiaries randomly by computer from a centralized list of eligible farmers. This list has been maintained for a number of years, and all households which cultivate land are considered eligible, so in practice the list covers nearly all households in rural areas.[7]

Before the start of the agricultural season each year, the government carries out a listing exercise to update its farmer list. This process involves verifying changes in household composition, and is also meant to ensure that there is only one beneficiary per household. Using this updated list, for each district, the government draws a random sample of farm-

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

[6]Several academic papers show that the allocation was subject to nepotism (Kilic et al. 2015, Lunduka et al. 2013, Holden and Lunduka 2012).

[7]Our data consists of a representative sample of villagers, and we find that 95% of households farm some land.

ers, in proportion to their farming population and the acreage under cultivation. Finally, within each district, the District Agriculture Development Office (DADO) distributes vouchers across villages through large public meetings, that are pre-announced over media and through extension officers.

During the time period that we study (2017-19), FISP included subsidies for pre-packaged quantities of 4 inputs (50 kg of NPK fertilizer, 50 kg of Urea fertilizer, 5 kg of hybrid maize seeds,[8] and 2 kg of hybrid legume seeds). The market value of this package was about \$75, and the FISP subsidy was worth approximately 75% of the cost (meaning a farmer redeeming a FISP voucher would have to pay approximately \$18 at a retail store 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 coupon must be redeemed in its entirety, i.e., it is not possible to redeem say, the NPK fertilizer coupon for less than 50 kg of NPK (which is likely the reason why there is widespread sharing of inputs).[9] Because the subsidy is generous, take-up traditionally is nearly universal. In our data covering 2017-19, we find that 94% of farmers who received coupons redeemed them.

3 Data

The surveys we use in this paper were collected for a randomized evaluation of unconditional cash transfers (disbursed by the NGO GiveDirectly) in Chiradzulu and Machinga districts in the Southern Region of Malawi. These areas were selected in collaboration with GiveDirectly and the funder (USAID) for a variety of reasons, including poverty levels, cell phone coverage, proximity to roads, and village size.[10] The villages are therefore not randomly selected but, as we show in Aggarwal et al. (2022c), the villages look similarly on observable characteristics

[8]Farmers could also choose to use this voucher for 7 kg of open pollinated variety (OPV) maize or sorghum seeds.

[9]In our data, however, we do find some farmers reporting redeeming quantities other than full bags. We attribute this to reporting errors.

[10]See Aggarwal et al. (2022a) for more details.

to the averages in those regions. The cash transfer evaluation included 300 villages.

We use surveys of households and of agricultural input dealers to conduct our analysis. First, to construct an analysis sample of households, we randomly selected 10 households per village in each of the 300 villages for comprehensive surveys. We successfully completed baseline surveys with 2,944 households, out of which 2,803 (95.2%) reported growing crops. Of these, 2,784 completed endline surveys. We restrict our sample to those household heads who are between 25 and 80 years of age, which is just over 89% of the full sample. Among these households, we make use of a baseline survey, conducted in April-July 2019 (which collected information on agricultural decisions for the 2017-18 and 2018-19 seasons), and an endline survey, conducted in April-July 2021, which collected information on the 2019-20 season (note that in 2020-21, the country transitioned out of FISP into the Affordable Input Program, which followed different targeting rules and is therefore, not part of this analysis). For the purpose of this paper the most important module is the agriculture section, which included detailed questions about FISP receipt, redemption, and subsidy sharing, as well as detailed questions on ultimate input usage (from FISP as well as market sources), yields, and questions on where households purchased inputs and the costs of accessing inputs (including travel costs). In addition, we use other questions in the survey, such as demographics and time-invariant background questions, to examine randomization balance.

Second, we conducted surveys of every agriculture input seller in the area (encompassing the 2 study districts as well as 7 contiguous districts.[11] To do this, we conducted a census of input sellers, and then followed up to conduct longer detailed surveys with each retailer. Of the 640 retailers identified in the census, we were able to follow up with 550 retailers for the longer surveys. However, we are able to include all 640 in the price dispersion analysis, since we collected information on the retail prices of fertilizer in the census.

[11]We included these neighboring districts to be able to accurately calculate price disperson within our study region, since farmers can in principle travel anywhere to access inputs and thus farmer near district borders may travel across them. The 7 districts are Balaka, Blantyre, Mangochi, Mulanje, Phalombe, Thyolo, and Zomba.

4 Targeting and the Effect of FISP on Input Usage

4.1 Were program rules followed?

As discussed above, FISP was traditionally targeted towards certain groups, such as older or resource-poor farmers, and in practice chiefs had discretion over distribution, so that subsidies were allocated to relatives and to farmers with higher returns to inputs. If FISP were truly random in 2017-19, we should observe no such correlation. To evaluate this, we check for balance between FISP beneficiaries and non-beneficiaries in Table 1. In the Table, Column 1 reports the mean while Columns 2-4 present different (multivariate) regressions of FISP on a set of predetermined characteristics, pooling the 3 seasons in which FISP was randomized (2017-18, 2018-19, and 2019-20). 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, age, household composition, years of education, and land. In addition, we control for whether the respondent had received FISP in the year prior to the program. Unexpectedly, we find several significant correlations. We see clear evidence that the chief (and spouse) are more likely to receive the coupon, and clear evidence that people receiving the coupon in the prior season were more likely as well. Therefore, our results show evidence consistent with some level of mistargeting.

In Column 3, we drop those who received the subsidy in the prior year, as well as households in which the respondent is the chief or spouse of chief. To be on the conservative side, we also drop those households where the respondent is the child of the chief, even though we do not find this variable to be statistically significant in determining the subsidy allocation. In all, these exclusions involve dropping a total of 22.2% of the sample.[12] We

[12]Note that while we drop 22% of the observations, we only drop 7% of the households in going from Column 2 to 3. This is because only those households that are related to the chief are being dropped entirely from the sample. Those households which received a FISP coupon in the prior year, get dropped for the year in question, but do remain in the estimation sample in other years.

find no significant correlation in this specification, although it is still the case that older household heads are more likely to receive the coupon. However, the effect is small (and insignificant): a standard deviation of age (about 15 years) raises the odds of receiving the coupon by 1.2 percentage points, on a base of 21.4% in Column 3 (i.e. about 5%). We keep this same sample restriction throughout the remainder of the paper, and control for age in our regressions.

Finally, as mentioned earlier, these regressions all include village fixed effects. While FISP was purportedly 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 could vary across villages. In Table A1 we show the same regressions without village fixed effects. While the pattern of coefficients is very similar, several are now significant (namely household age and education). The coefficients are still fairly small but for this reason we prefer to use village fixed effects.

Table 1: FISP Randomization Check

	Mean (std. dev.)	Coefficients from multivariate regression	
	(1)	(2)	(3)
=1 if chief and spouse	0.03	0.148	
	(0.16)	(0.033)	
=1 if chief's child	0.02	0.034	
	(0.15)	(0.030)	
=1 if chief's other relationships	0.45	0.009	0.014
	(0.50)	(0.013)	(0.014)
Household head age (in 10 yrs)	4.55	0.011	0.008
	(1.37)	(0.004)	(0.005)
=1 if female headed household	0.39	0.011	0.016
	(0.49)	(0.012)	(0.012)
Household size	5.07	0.002	0.004
	(2.04)	(0.003)	(0.003)
Respondent years of education	4.53	-0.000	0.000
	(3.38)	(0.002)	(0.002)
=1 if household owns farm land	0.94	0.039	0.035
	(0.23)	(0.032)	(0.035)
Farm land size (acres)	1.21	0.006	0.008
	(1.06)	(0.006)	(0.006)
FISP coupon received last year	0.18	0.059	
	(0.39)	(0.014)	
Households		2496	2331
Observations	7370	7370	5731

Notes: FISP indicator takes value as 1 if household received a FISP coupon (any of maize, legumes, Urea, and NPK), and 0 otherwise. The percentage of households that received FISP was 23.6% in Column 2 and 21.4% in Column 3. Data pooled for three agricultural seasons, 2017/18-2019/20. Column 3 includes full sample but restricted to households did not receive FISP vouchers in last year. Column 1 shows control mean and standard deviations, whereas columns 2 onwards show coefficients from regressions of FISP status on household characteristics as shown in rows. Regressions include village and year fixed effects and standard errors clustered at the village level and are in parentheses.

4.2 Effect of FISP on contemporaneous fertilizer usage

As mentioned earlier, take-up of FISP is close to universal: over 2017-19, we find that 94% of beneficiaries redeemed their coupons. As such, we expect FISP to have a large effect on input adoption, despite the high baseline rate of fertilizer usage (79% of the control group used fertilizer in any given year). To examine the effect of FISP on current-season adoption (note that we can't examine lasting effects, because we drop those that receive the year before), we run variations on the following regression:

$$Y_{ivt} = \beta \; FISP_{ivt} \; + \; \gamma \; X_i \; + \phi_v + \; \theta_t \; + \; \varepsilon_{it} \tag{1}$$

where Y_{ivt} is a measure of input adoption (across *all* types of fertilizer, including market and non-market fertilizer) for household i in village v in year t, $FISP_{ivt}$ is an indicator for whether the household received FISP in that year, and ϕ_v and θ_t are village and year fixed effects. We run this regression with and without household characteristics X_{iv}. Controls include an indicator for whether the household is female headed, age, household size, years of education, whether the household head is related to chief (though recall that the chief him or herself, his spouse, and his children are excluded), and farm land size.

Second we run a specification utilizing only within-household variation by including household fixed effects μ_i

$$Y_{ivt} = \beta \; FISP_{it} \; + \; \gamma \; X_i \; + \; \theta_t + \mu_i + \varepsilon_{ivt} \tag{2}$$

We focus on chemical fertilizer in this analysis, because fertilizer is a standardized product, whereas there are several different types of seeds that are available, which may not be comparable to one another. We show results for 2 types of fertilizer, NPK and Urea; while these 2 types are very different from one another, within each category varieties are chemically indistinguishable across locations. Results are shown in Table 2. While input usage in the control group is already relatively high (79% of farmers use fertilizer, and the average unconditional quantity is 49.5 kg), FISP still has a large effect, raising input usage by 10-13 percentage points, and quantities by 13-15 kg. Comparing columns, we see that including household fixed effects attenuates treatment effects somewhat, though all outcomes are highly statistically significant with or without fixed effects.[13]

Table 2: FISP and Contemporaneous Input Adoption

	=1 if used input from any source			Total input used on own plot (FISP + market combined) (kg)		
	(1)	(2)	(3)	(4)	(5)	(6)
FISP coupon recipient current year	0.13	0.13	0.10	15.40	14.76	13.34
	(0.01)	(0.01)	(0.01)	(1.85)	(1.83)	(1.94)
Control mean: Dependent variable	0.79	0.79	0.79	49.00	49.00	49.00
Observations	5731	5731	5731	5731	5731	5731
Household controls	N	Y	N	N	Y	N
Household FE	N	N	Y	N	N	Y

Notes: Data pooled for three agricultural seasons, 2017/18; 2018/19; and 2019-20. Columns 2 and 5 include additional controls for household characteristics. Columns 3 and 6 include household fixed effects. Household characteristics include an indicator for whether household is related to village chief, female headed household, age of the household head, household size, respondent's years of education, and farm land size in acres. Farm land size winsorized at 99%. Standard errors clustered at household level and all regressions include village and year fixed effects.

In Table A2, we examine quantities of market and FISP fertilizer. We find that the control group buys on average of 28.2 kg of unsubsidized fertilizer from the market, and this declines significantly by 18-19 kg in the FISP group. By contrast, FISP fertilizer usage is 21 kg in the control group (this is due to the widespread sharing of subsidies – we return to this issue later), but FISP beneficiaries use 32-33 kg more. Thus, we find that about 60% (19 kg out of 32 kg) of FISP fertilizer crowds out market fertilizer, nevertheless still netting a substantial 13 kg increase in usage.[14]

[13]It would be interesting to examine whether this translates into sustained usage (as in Carter et al. 2021 and Fishman et al. 2021), but we are unable to do this, because as discussed earlier, we find autocorrelation in subsidy receipt and thus exclude people who received FISP in the prior year.

[14]Note also that, in the absence of the program, there would be no FISP to share with the control group, so the aggregate effects of the program are much larger than 13 kg per beneficiary.

5 Subsidies and the Remoteness Gradient

Having demonstrated the basic impacts of the FISP program, we move on to our primary research question, which is to document how subsidies affect the input adoption-remoteness gradient. The mechanics of this analysis are similar to prior work in Tanzania, Liberia and Malawi (Aggarwal et al. 2022b, Kapoor et al. 2022), and we briefly describe the concepts mentioned in that paper, before turning to our main specification.

5.1 Defining remoteness

As in prior work, we use two measures of remoteness for village v, both defined in relation to the local population centers, or "hubs": 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. In the first, we define the remoteness of village v as a simple population weighted distance to each hub:

$$remoteness_v = \sum_h d_{hv} pop_h \tag{3}$$

where pop_h is the (relative) population of hub h (i.e. the population of that hub divided by the population of all hubs) and d_{hv} is distance from village v to hub h. The second measure is similar to Donaldson and Hornbeck (2016) and measures market access for each village as follows:

$$MA_v = \sum_h \tau_{hv}^{-\theta} pop_h \tag{4}$$

MA_v includes population weights as measures of the relative importance of each hub. These weights are adjusted by their elasticity-adjusted trade costs of reaching each hub, $\tau_{hv}^{-\theta}$.[15]

[15] $\tau_{hv} = 1 + \frac{2.42 * cost_{hv}}{avgprice}$, where $cost_{hv}$ is the cost of accessing that hub, and 2.42 is the estimated number of times required to incur that cost (in our data, we observe that the cost of the trip coming from the agro-dealer is 40% higher than the cost incurred while going because farmers also have to pay extra fare

We standardize both measures to have mean 0 and standard deviation 1 (and put a negative sign in front of MA_v, so that it measures remoteness rather than market access). The distributions of these variables are illustrated in Figure A2. The population-weighted distance to hubs has a wider range (running from about -1.5 to 4 standard deviations, compared to -2 to 2 for the elasticity-adjusted travel cost to hub. Nevertheless, using either measure, there is substantial variation in remoteness in the sample. While a visual examination of Figure A2 shows a fair degree of comovement in the two remoteness proxies, we also formally examine their correlation in Table A3, finding a coefficient of 0.6.

Table A4 shows the relationship between farmers' characteristics and remoteness measures for all the covariates that we show in Table 1. We find several significant correlations: farmers in more remote villages are less likely to be female-headed, and have fewer years of education. While our focus ultimately is on the FISP interaction (which is randomized *within* village and not *across*), all regressions have versions with household controls that control for the full list of covariates presented in Table A4.

5.2 Measuring travel costs

To estimate travel costs, we use two sources of data. First, we use the Google Maps API to estimate driving times from every village in our sample to every agricultural input dealer. In the data, Google labels driving sections as being on M, S, or T roads. This classification system is based on a British system, where M roads are main roads (primarily paved), and S (secondary) and T (tertiary) are local feeder roads. We check the robustness of this methodology by using survey data from our respondents, where we asked them about travel costs to the nearest hub. Second, we use travel costs measured in our surveys. In particular, we asked respondents to record each trip they took to purchase inputs. In this module, we recorded the location (and name, where possible) of the input dealer, as well as the cost of travel (as well as all other details of the transaction).

for the bag of fertilizer. *avgprice* is the average price of fertilizer in the sample. For $-\theta$, we appeal to the substitution elasticity across agrovets which is estimated in Tanzania to be -7.9.

We then regress travel costs (to the ag dealer and to hubs) against Google distances. Results are shown in Table A5 and are generally intuitive, that costs are 3-5 times higher on T roads than on the other roads (which are mostly indistinguishable from one another). The average one-way trip to the agro-retailer costs \$1.09 (implying approximately \$2.62 for a round-trip with a bag of fertilizer on the way back) and to the hubs costs \$2.91.

5.3 Defining travel cost-adjusted prices

We define the relevant travel cost-adjusted price that farmers must pay in two ways. This analysis is at the village level, because our measures of access only vary at that level. In general, the village would also be the most meaningful and policy-relevant location to define "access" in a rural context. First, we assume that farmers are free to travel anywhere to buy inputs, and must incur the transportation cost as calibrated above. With this concept, we calculate the minimum travel cost-adjusted price that is available to villagers from v as follows:

$$p_v^{min} = \min_j \{r_j + c_{vj}\} \tag{5}$$

where r_j is the price at agrovet j and c_{vj} is the cost of traveling to agrovet j, and returning to village v with a bag of fertilizer. Using our Tanzania data, we estimate that farmers must make a round-trip for themselves, and a one-way trip for the bag of fertilizer, which we estimate from surveys to cost 70% as much as the farmer's fare, implying that the travel cost must be incurred approximately 2.4 times.

Our second measure is relevant if farmers may make decisions using a simpler decision rule by simply choosing the nearest retailer (so that prices at all retailers other than the nearest are irrelevant). Under this decision rule, the travel cost adjusted price that farmers face is

$$p_v^{nearest} = r_v^{nearest} + c_v^{nearest} \tag{6}$$

This analysis is very similar to that in our prior work, but is for *subsidized* fertilizer. To calculate the subsidized price, we take the market price from the ag dealer census data, and subtract the FISP coupon subsidy (15,000 MWK per bag). Figure A1 plots the distribution of travel cost-adjusted prices. As in our prior work, there is clear heterogeneity: the price at the 90th percentile is about \$11.5 compared to \$7.1 at the 10th percentile. The heterogeneity is notable in this context because the dispersion comes almost entirely from travel costs: retail price heterogeneity is minimal in this setting (discussed in more detail later).

We do this calculation with both types of fertilizer, NPK and Urea, as both are used at similar rates by farmers. Results are very similar with either variety, because both are widely available at the same shops, so the travel costs are the same, and thus farmers will choose the same dealer for both types. The only difference is that the retail price for Urea is about \$3 less than NPK, and thus ad-valorem costs would appear larger. For easy readability, we show the (conservative) results with NPK in the main text (Table 3) and those with urea in the appendix (Table A6). We limit our discussion primarily to NPK.

5.4 Remoteness and prices

Table 3 shows the relationship between remoteness and various measures of access to inputs, including travel cost-adjusted prices, at the village level. First, we use our data to corroborate the anecdotal evidence that Malawi has a well-developed and deep input market (likely because of the long-standing FISP program, due to which there is enough demand for fertilizer to make it profitable for multiple fertilizer sellers to enter the market and compete with each other). Specifically, we find that 85% of the villages in our sample are within 10 kms of an agrodealer, and the average distance to the nearest agrodealer is about 7 kms with a somewhat large standard deviation of 4.5 kms. In contrast, in our work in Tanzania, we find that these numbers are respectively, 62% and 13 kms (Aggarwal et al. 2022b). However, despite the existence of a robust market, we observe a large remoteness penalty. A standard deviation increase in the remoteness measures leads to a 14-21 pp decline in the likelihood of having an agrodealer within 10 kms of the village. The distance to the nearest agro-retailer also increases substantially, with every standard-deviation of remoteness adding between 1.7 and 2.8 kms to the mean of 6.8 kms.

We then turn to analyzing prices in Panels B1 and B2 of both of these tables. The first thing we note in Table A6 is that despite its input market depth, Malawi has much higher fertilizer prices on average than the world price of fertilizer, which was about $13 for 50 kg of urea during this period; while in our sample, the subsidized price at the shop is $4.6, which points to a sticker price of about $19, nearly 50% higher than the world price. Fertilizer is expensive in Africa in general because much of the fertilizer used on the continent is imported from abroad, and the fact that Malawi is landlocked, likely drives up the average price level further.[16] That said, as a result of the highly developed input market in the country, we observe almost no gradient at all in the subsidized (or retail) *pecuniary* price of fertilizer. However, there is a clear remoteness penalty in travel costs to the retailer, which go up by a dollar for every SD increase in remoteness (on a base of about $3). This is a substantial cost, relative to the price of fertilizer, implying that the ad-valorem cost for a bag of fertilizer is about 13 percentage points higher for every standard deviation of remoteness.[17]

[16]While not the central point of this paper, this further underscores the double whammy of remoteness in these areas.

[17]In Aggarwal et al. (2022b), we estimate that the ad valorem trade costs in Tanzania as revealed by the choices made by farmers are about 4 times higher than the measured pecuniary trade costs. There may be many reasons behind this divergence, such as uncertainty about stock-outs at a far-away dealer or simply, unavailability of reliable transport to travel beyond a particular distance. Given the depth of the market in Malawi, the non-pecuniary costs are likely lower, but are likely non-zero. Therefore, these pecuniary costs still represent only a lower bound of the costs faced by farmers.

Table 3: Remoteness and price heterogeneity for subsidized fertilizer (NPK)

	Mean (std. dev.)	Population-weighted distance to hubs	Elasticity-adjusted travel cost to hubs
	(1)	(2)	(3)
Panel A. Summary measures of access to input retailers			
Has an agrodealer within 10 km	0.85	-0.21	-0.16
		(0.02)	(0.02)
Distance to nearest agro-retailer	6.82	2.82	2.04
	(4.49)	(0.20)	(0.23)
Panel B1. Travel-cost adjusted prices faced by farmers			
Minimum travel cost-adjusted price for a 50-kg bag of fertilizer using FISP coupon	9.06	1.20	1.45
	(1.84)	(0.08)	(0.07)
Decomposition of price			
Subsidized price for a 50-kg bag of fertilizer using FISP coupon	6.06	0.00	0.00
	(0.12)	(0.01)	(0.01)
Minimum travel cost to an agro-retailer	3.00	1.20	1.44
	(1.84)	(0.08)	(0.07)
Panel B2. Travel-cost adjusted prices at the nearest agro-input shop			
Travel cost-adjusted price for a 50-kg bag of fertilizer using FISP coupon	11.27	1.94	1.98
	(2.65)	(0.11)	(0.10)
Decomposition of price			
Subsidized price for a 50-kg bag of fertilizer using FISP coupon	8.46	0.35	0.52
	(0.97)	(0.05)	(0.05)
Travel cost to the nearest agro-retailer	2.81	1.58	1.46
	(2.14)	(0.08)	(0.09)
Observations	300	300	300

Notes: Unit of observation is the village. Data is for the 2018-19 season. The mean is listed in Column 1. Remoteness measures are standardized variables measured at the village level as standard deviation units away from mean value.

5.5 Remoteness, redemption, sharing and input use

Redemption

Take-up of FISP is high but not universal, around 94%; and as shown above, remote farmers face substantially higher travel costs to access a retailer. The first question therefore is whether these costs are an impediment to redemption, which we show in Table 4. In the Table, we show results for both measures of distance (each entry represents a separate regression). The odd-numbered columns show regressions without controls, while the even-numbered columns control for the background characteristics listed in Table A4.

Table 4: Remoteness and Coupon Redemption

	Probability of Redemption		Quantity redeemed (kg)	
	(1)	(2)	(3)	(4)
Population-weighted distance to hubs	-0.02	-0.02	-4.89	-4.76
	(0.01)	(0.01)	(1.03)	(1.03)
Elasticity-adjusted travel cost to hubs	-0.02	-0.02	-3.72	-3.62
	(0.01)	(0.01)	(0.90)	(0.93)
Mean	0.94		74.73	
Observations	1226	1226	1226	1226
Household controls	N	Y	N	Y

Notes: Regressions are restricted to FISP beneficiaries. The dependent variable in Columns 1-2 is an indicator for redeeming FISP, while in Columns 3-4 it is the quantity redeemed. See text for definition of remoteness measures. Data pooled for three agricultural seasons, 2017/18-2019/20. All regressions include year fixed effects. Standard errors clustered at the village level are in parentheses.

We start by documenting that FISP redemption is lower in remote areas, though the effect is small. A standard deviation increase in remoteness is associated with a 2 percentage point decline in redemption. In terms of quantities, this amounts to a decline of about 5 kg, on a base of 75 kg (roughly 7%). This can amount to a fairly large difference over the full range of the distribution, for example in Figure A2, the most and least remote villages are about 4-5 standard deviations apart using the two measure of remoteness. This translates to an 8-10 pp difference in the extensive margin of redemption and of 20-25 kgs in the intensive margin of redemption between the least and the most remote villages.

Sharing

Next we examine how remoteness affected sharing in Table 5. In this Table, Columns 1-2 shows the amount that non-beneficiaries report receiving, while Columns 3-4 shows the amount that beneficiaries report giving. With a representative sample of farmers, if reporting were perfect, then these quantities should match. In particular, since 24% receive the subsidy, then the per-farmer quantity received by non-beneficiaries should be about 1/3 of the per-farmer quantity shared by beneficiaries. However, these quantities may differ if people are hesitant to report sharing (since it is officially not allowed), or if people do not report shared quantities as part of their redemption in the first place (i.e. they only report redemption on that which they kept for themselves). For this reason, we conjecture that the quantities reported by non-beneficiaries might be more accurate.[18]

In Columns 1-2, we see that non-beneficiaries report receiving an average of 21 kg, while in Columns 3-4 beneficiaries report giving only 13 kg (which imply only about $0.24/0.76 * 13 \simeq 4.1$ kg per non-beneficiary). This discrepancy is likely indicative of under-reporting among beneficiaries, though we have no objective data to know for sure. Of most importance to this paper, however, is that both measures clearly show that sharing is reduced in remote areas. Relative to mean shared amounts, the effects are large, ranging from a reduction of 25-50% in Columns 1-2 and 40-65% in Columns 3-4.

[18]Using the information reported by the non-beneficiaries on quantities shared also helps us fully account for the intensive margin of redemption. Specifically, the average of the quantity redeemed is 75 kg, with a redemption rate of 94%. Since a bag of fertilizer can only be redeemed in its entirety, this avaerage sgould work out to 94 kg. On the sharing side, beneficiaries (who form a quarter of any village) report sharing 13 kgs on average, while non-beneficiaries (about 75%) of any village) report receiving 20 kg on average, a discrepancy of about 21 kg per beneficiary (7 kg difference each for 3 non-beneficiaries), which is nearly identical to the observed redemption gap.

Table 5: 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)
Population-weighted distance to hubs	-4.66	-3.94	-5.73	-5.22	0.85	0.46
	(0.57)	(0.56)	(0.99)	(0.99)	(1.23)	(1.20)
Elasticity-adjusted travel cost to hubs	-9.27	-9.18	-8.57	-8.44	4.85	4.82
	(0.78)	(0.81)	(0.89)	(0.94)	(1.08)	(1.10)
Household controls	N	Y	N	Y	N	Y
Mean	20.77		13.11		61.62	
Observations	4505	4505	1226	1226	1226	1226

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 respective dependent variable on remoteness measure. The dependent variable in Columns 1-2 is the quantity of FISP fertilizer bought by non-beneficiaries. See text for definition of remoteness measures. Data pooled for three agricultural seasons, 2017/18-2019/20. All regressions include year fixed effects. Standard errors clustered at the village level are in parentheses.

Compared to redemption amounts, the reduction in Columns 3-4 is about the same size as the reduction in redemption for the population-weighted distance, but is actually larger for the elasticity-adjusted measure. This means that the residual amount actually used on the farm (which we show in Columns 5-6) shows no gradient for the population-weighted distance measure, but actually shows an *increase* for the elasticity-adjusted measure (equivalent to about 8% of the baseline mean). While we do not wish to put too much weight on this result, we do view the reduction in sharing as an important channel in the context of this program.

Input usage - remoteness gradient

The above results show either no gradient or a positive gradient between remoteness and ultimate usage. And since FISP is a large amount of fertilizer (the average amount used from FISP is about 55 kg, which is higher than what the control group uses in total), FISP should have a large impact on reducing the input adoption-remoteness gradient that has been documented in Tanzania (Aggarwal et al. 2022b), Malawi and Liberia (Kapoor et al. 2022). We explore this formally below.

In particular, we run the following regression:

$$Y_{ivt} = \beta R_v + \gamma FISP_{ivt} + \delta FISP_{ivt} * R_v + \gamma X_{iv} + \mu_v + \phi_t \; + \; \varepsilon_{ivt} \tag{7}$$

where Y_{ivt} is the quantity of input used 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 and ϕ_t are year fixed effects. Standard errors are clustered at the village level. We show results both with and without village fixed effects: μ_v. 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 6.

To start, we show that remote FISP non-beneficiaries use less fertilizer: one standard deviation of remoteness is associated with an 13-14 percentage point decline in the likelihood of using fertilizer, and about a 10-11.5 kg decline in input usage (on a 49 kg base). However, for FISP beneficiaries, this gradient is indistinguishable from zero (we show p-values at the bottom of the table). Including village fixed effects has a modest effect on the coefficients, but they continue to be economically meaningful (note that the uninteracted remoteness coefficients cannot be estimated with village fixed effects as remoteness is defined at the village level).

Table 6: FISP and the Input Adoption-Remoteness Gradient

	=1 if input used from any source				Total input used on own farm from all sources (kg)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FISP coupon recipient current year	0.17	0.14	0.17	0.15	17.84	15.73	18.07	16.52
	(0.01)	(0.01)	(0.01)	(0.01)	(1.74)	(1.73)	(1.65)	(1.66)
Standardized Measure of distance and interactions								
Population-weighted distance to hubs	-0.14				-11.68			
	(0.01)				(0.95)			
FISP × Population-weighted distance to hubs	0.13	0.12			9.89	9.35		
	(0.01)	(0.01)			(1.60)	(1.52)		
Elasticity-adjusted travel cost to hubs			-0.13				-11.90	
			(0.01)				(1.18)	
FISP × Elasticity-adjusted travel cost to hubs			0.13	0.10			13.05	11.42
			(0.01)	(0.01)			(1.60)	(1.59)
p-value: Distance + (FISP × Distance)	0.50		0.48		0.22		0.42	
Control mean: Dependent variable	0.79	0.79	0.79	0.79	49.00	49.00	49.00	49.00
Observations	5731	5731	5731	5731	5731	5731	5731	5731
Household controls	Y	Y	Y	Y	Y	Y	Y	Y
Village FE	N	Y	N	Y	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: All columns include year fixed effects and household controls (female headed household, age of the household head, household size, respondent's years of education, whether the household is related to chief, and farm land size in acres, winsorized at 99%). In addition, the even-numbered columns include village fixed effects. Data pooled for three agricultural seasons, 2017/18-2019/20. Remoteness is measured at village level, standardized to have mean zero and standard deviation one. Standard errors clustered at village level are in parentheses.

These results imply that FISP completely eliminates the input adoption gradient. However, it is important to note that the presence of widespread sharing complicates this comparison somewhat, in particular because non-beneficiaries in remote areas are less likely to receive a share of inputs, and thus part of the gradient operates via subsidized inputs even for non-beneficiaries. Thus the results are contextually different from prior work such as Aggarwal et al. (2022b) which took place in rural Tanzania where inputs were not subsidized. In Malawi, however, the effect or remoteness must be understood in the context of FISP;

this is a big part of the reason for why, while the remoteness gradient in usage is similar, levels of usage are far higher than in many other contexts.

6 Discussion and Conclusion

Fertilizer subsidies are one of the most common policy tools to increase input usage in developing countries. We take advantage of a unique policy experiment in which the government of Malawi randomly allocated subsidies to households over a 3-year period. In the first part of the analysis, we document that despite substantially crowding out market purchases, the program nevertheless dramatically increased input usage. We document, as prior work has, that subsidies are widely shared within villages, though this is not enough to equalize input usage between beneficiaries and non-beneficiaries. However, the presence of sharing does mean that the impact of subsidies is understated in this context as compared to a counterfactual world without subsidies (since the control group also benefits from the program).

The main part of our analysis features two main results that were not necessarily obvious at the outset of our analysis, and which have important implications for subsidy policy design in the developing world. The first is that despite the higher pecuniary and non-pecuniary costs involved in redeeming the subsidy for beneficiaries located in remote villages, redemption rates are similar across the spatial distribution of villages. This result stands in some contrast to earlier work showing how small costs discourage adoption of a variety of products, largely in the context of preventive health (i.e. Cohen and Dupas 2010, Ashraf et al. 2010, Kremer and Miguel 2007, Ashraf et al. 2013, Meredith et al. 2013), as well as some in the context of financial products (i.e., Cole et al. 2013). Thus, our findings allow us to temper somewhat the conclusions from the literature on subsidized provision because in this context at least, the relatively modest travel cost is not enough to discourage usage, perhaps because the subsidy is so large and because fertilizer is so highly valued. Our results therefore, suggest that the discouraging effects of travel costs or co-pays depend on contextual details.

Second, we find strong evidence that there is less inter-household sharing of subsidized inputs in remote villages. While it is unclear to us what drives this behavior,[19] it presents a clear policy lever. One policy implication suggests that simple adjustments to the FISP randomization that leverage these spatial differences in sharing may spread the benefits of the subsidy program more equally across villages. For example, consider a goal in which policymakers wish for the average quantity used by farmers through FISP to be equal across villages. If so, the policymaker should increase the probability of receiving FISP by 9-20 pp with each standard deviation of remoteness.[20] Further refinements of policy could more precisely allocate coupons based on the transaction costs associated with redemption, or proximity of agroretailers to each village.

Taken together, our results suggest that not only has FISP been successful in achieving its stated goal of enhancing input usage for beneficiaries, it has also had positive spillover effects for non-beneficiaries. Moreover, its input usage effects are disproportionately larger in remote areas, leading to spatial convergence and suggesting that subsidy policies can be designed with a view of narrowing spatial inequities.

[19]If anything, economic theory as well as prior literature predict that kinship norms should be stronger in remote areas with poorer access to markets (e.g, Platteau 2006).

[20]These estimates are obtained from differentiating $E[Q] = E[Q|FISP] \cdot \Pr(FISP) + E[Q|NoFISP] \cdot (1 - \Pr(FISP))$ with respect to remoteness R, and solving for $\frac{d\Pr(FISP)}{dR}$ such that $\frac{dE[Q]}{dR} = 0$.

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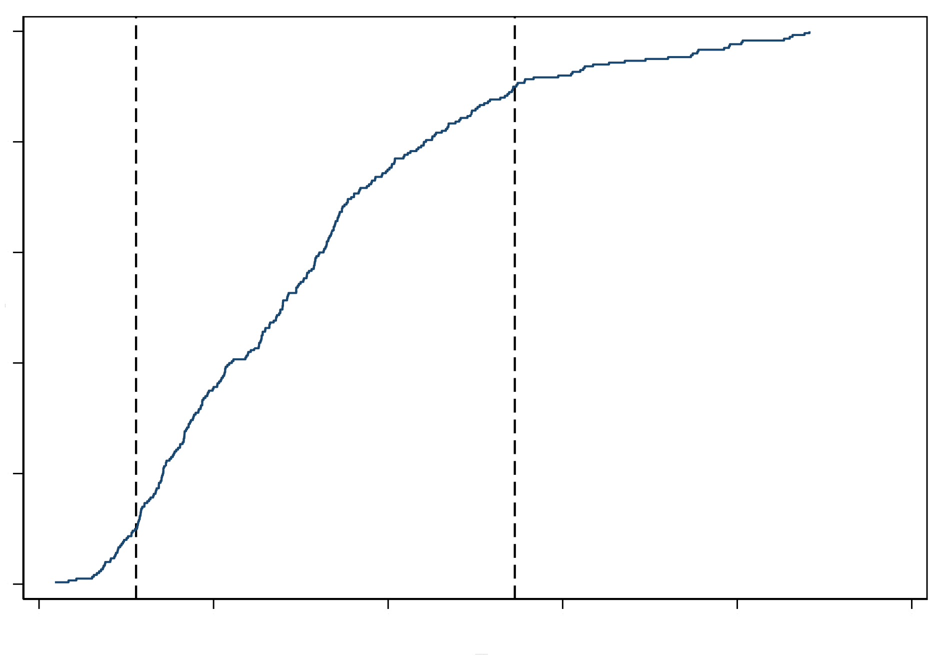
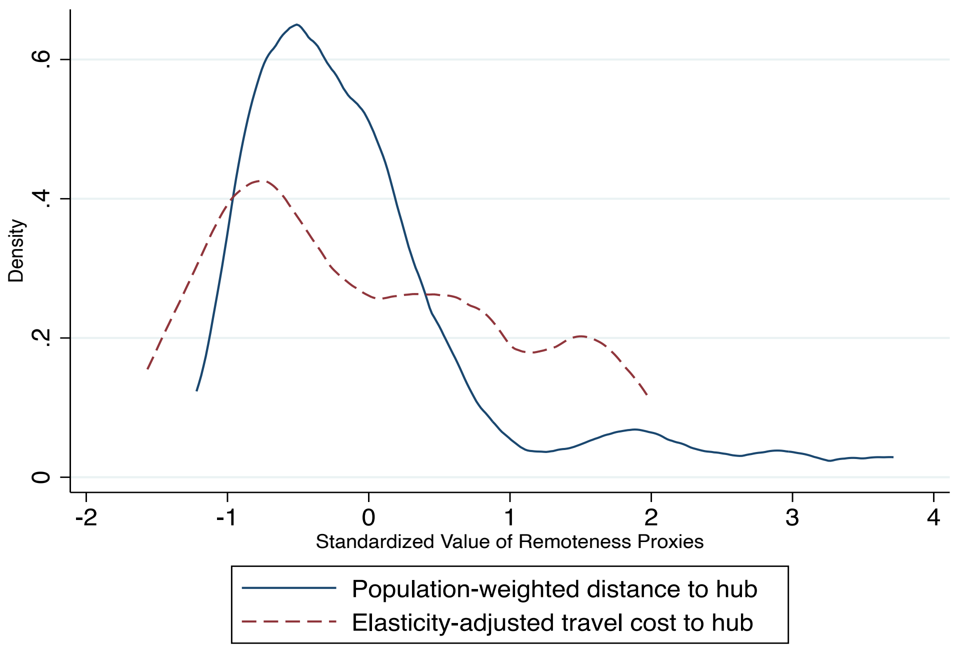
Appendix

Figure A1: CDF for Travel Cost-Adjusted Price of Fertilizer Under FISP Program



Note: Figure presents the CDF of the travel cost-adjusted price for FISP fertilizer. The unit of observation if the village (N=300).

Figure A2: The Distribution of Remoteness Proxies



Note: The distribution of remoteness proxies is depicted at the village level (N=300).

Table A1: FISP Randomization Check (without Village Fixed Effects)

	Mean (std. dev.)	Coefficients from multivariate regression	
	(1)	(2)	(3)
=1 if chief and spouse	0.03	0.154	
	(0.16)	(0.033)	
=1 if chief's child	0.02	0.014	
	(0.15)	(0.028)	
=1 if chief's other relationships	0.45	0.007	0.005
	(0.50)	(0.011)	(0.012)
Household head age (in 10 yrs)	4.55	0.017	0.015
	(1.37)	(0.004)	(0.004)
=1 if female headed household	0.39	0.011	0.018
	(0.49)	(0.011)	(0.012)
Household size	5.07	-0.005	-0.003
	(2.04)	(0.003)	(0.003)
Respondent years of education	4.53	0.003	0.004
	(3.38)	(0.002)	(0.002)
=1 if household owns farm land	0.94	0.027	0.027
	(0.23)	(0.031)	(0.033)
Farm land size (acres)	1.21	-0.002	0.003
	(1.06)	(0.005)	(0.006)
FISP coupon received last year	0.18	0.108	
	(0.39)	(0.014)	
Households		2496	2331
Observations	7370	7370	5731

Notes: FISP indicator takes value as 1 if household received a FISP coupon (any of maize, legumes, Urea, and NPK), and 0 otherwise. The percentage of households that received FISP was 23.6% in Column 2 and 21.4% in Column 3. Data pooled for three agricultural seasons, 2017/18-2019/20. Column 3 includes full sample but restricted to households did not receive FISP vouchers in last year. Column 1 shows control mean and standard deviations, whereas columns 2 onwards show coefficients from regressions of FISP status on household characteristics as shown in rows. Regressions include year fixed effects and standard errors clustered at the village level and are in parentheses.

Table A2: Crowd-out of Market Inputs

	Input bought at market price (kg)			Subsidized Input bought from FISP (kg)		
	(1)	(2)	(3)	(4)	(5)	(6)
FISP coupon recipient current year	-17.46	-18.03	-19.02	32.86	32.79	32.37
	(1.49)	(1.48)	(1.73)	(1.72)	(1.73)	(1.99)
Control mean: Dependent variable	28.23	28.23	28.23	20.77	20.77	20.77
Observations	5731	5731	5731	5731	5731	5731
Household controls	N	Y	N	N	Y	N
Household FE	N	N	Y	N	N	Y

Notes: Data pooled for two agricultural seasons, 2017/18-2018/19. Columns 2 and 4 include additional controls for household characteristics. Columns 3 and 6 include household fixed effects. Household characteristics include female headed household, age of the household head, household size, respondent's years of education, whether household is related to chief, and farm land size in acres, winsorized at 99%. Farm land size winsorized at 99%. Standard errors clustered at household level and are in parentheses.

Table A3: Correlation Between Proxy Measures

	Population-weighted distance to hubs
Elasticity-adjusted travel cost to hubs	0.60
	(0.05)
Dependent variable mean	-0.00
Independent variable mean	-0.00
Observations	300

Notes: The regression is run at the village level. See text for definition of remoteness measures.

Table A4: Remoteness and Household Characteristics

	Mean (std. dev.)	Population-weighted distance to hubs	Elasticity-adjusted travel cost to hubs
	(1)	(2)	(3)
=1 if chief's other relationships	0.47	0.07	0.03
	(0.50)	(0.05)	(0.07)
Household head age (in 10 yrs)	4.49	0.12	0.39
	(1.35)	(0.09)	(0.15)
=1 if female headed household	0.39	-0.07	-0.05
	(0.49)	(0.03)	(0.05)
Household size	5.06	0.20	0.37
	(2.03)	(0.15)	(0.24)
Respondent years of education	4.53	-1.13	-1.67
	(3.40)	(0.27)	(0.37)
=1 if household owns farm land	0.94	-0.00	0.00
	(0.24)	(0.01)	(0.02)
Farm land size (acres)	1.19	-0.10	0.13
	(1.05)	(0.07)	(0.12)
Observations	5731	5731	5731

Notes: Remoteness measures are standardized variables measured at the village level as standard deviation units away from mean value. Major population hubs include Blantyre, Lilongwe, and Zomba. Data pooled for three agricultural seasons, 2017/18-2019/20. All regressions are bivariate with dependent variable in rows and include year fixed effects. Standard errors clustered at the village level and are in parentheses.

Table A5: Calibrating Travel Costs

	Mean (SD)	One-way per KM cost to Agro-retailers (USD)*		One-way per KM cost to Major Hubs (USD)	
	(1)	(2)	(3)	(4)	(5)
Distance to Hubs in KMs	11.1	0.05		0.04	
	(11.53)	(0.004)		(0.001)	
Distance to Hubs via M type road	2.3		0.02		0.03
	(5.28)		(0.007)		(0.001)
Distance to Hubs via S type road	1.6		0.02		0.06
	(6.14)		(0.007)		(0.006)
Distance to Hubs via T and unnamed road	7.2		0.10		0.06
	(6.25)		(0.007)		(0.004)
Observations	1132	578	578	3723	3723

Regressions are run at the village-destination level. The average total one-way cost to agro-retailers was $1.09 (which implies $2.62 round trip for the farmer and a bag of fertilizer), while the average one-way cost to the hub was $2.91. Standard errors clustered at village level are in parentheses.

Table A6: Remoteness and price heterogeneity for subsidized fertilizer (Urea)

	Mean (std. dev.)	Population-weighted distance to hubs	Elasticity-adjusted travel cost to hubs
	(1)	(2)	(3)
Panel A. Summary measures of access to input retailers			
Has an agrodealer within 10 km	0.85	-0.21	-0.16
		(0.02)	(0.02)
Distance to nearest agro-retailer	6.82	2.82	2.04
	(4.49)	(0.20)	(0.23)
Panel B1. Travel-cost adjusted prices faced by farmers			
Minimum travel cost-adjusted price for a 50-kg bag of Urea fertilizer using FISP coupon	7.61	1.23	1.53
	(1.91)	(0.08)	(0.07)
Decomposition of price			
Subsidized price for a 50-kg bag of Urea fertilizer using FISP coupon	4.63	0.01	0.02
	(0.05)	(0.00)	(0.00)
Minimum travel cost to an agro-retailer selling Urea	2.97	1.22	1.51
	(1.89)	(0.08)	(0.07)
Panel B2. Travel-cost adjusted prices at the nearest agro-input shop			
Travel cost-adjusted price for a 50-kg bag of Urea fertilizer using FISP coupon	9.75	1.84	1.95
	(2.66)	(0.11)	(0.10)
Decomposition of price			
Subsidized price for a 50-kg bag of Urea fertilizer using FISP coupon	6.96	0.46	0.62
	(1.30)	(0.07)	(0.07)
Travel cost to the nearest agro-retailer selling Urea	2.79	1.38	1.33
	(1.97)	(0.08)	(0.08)
Observations	300	300	300

Notes: Unit of observation is the village. Data is for the 2019-20 season. The mean is listed in Column 1. Remoteness measures are standardized variables measured at the village level as standard deviation units away from mean value.