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Variable Returns to Fertilizer Use and Its Relationship to Poverty

Experimental and Simulation Evidence from Malawi

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ABSTRACT

Despite the rise of targeted input subsidy programs in Africa over the last decade, several questions remain as to whether low and variable soil fertility, frequent drought, and high fertilizer prices render fertilizer unprofitable for large subpopulations of African farmers. To examine these questions, we use large-scale, panel experimental data from maize field trials throughout Malawi to estimate the expected physical returns to fertilizer use conditional on a range of agronomic factors and weather conditions. Using these estimated returns and historical price and weather data, we simulate the expected profitability of fertilizer application over space and time. We find that the fertilizer bundles distributed under Malawi's subsidy program are almost always profitable in expectation, although our results may be reasonably interpreted as upper-bound estimates among more skilled farmers given that the experimental subjects were not randomly selected. These results are robust to a tripling of fertilizer prices, to a 50 percent decrease in the maize price, and to drought conditions. We then correlate estimated expected returns to fertilizer use with geographically disaggregated estimates of headcount poverty rates. We find a very weak positive correlation between poverty and the expected returns to fertilizer, which calls into question how spatially distributionally progressive fertilizer subsidies are in helping to reduce poverty among Malawian farmers.

Keywords: Malawi, fertilizer, subsidy, poverty mapping

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1. INTRODUCTION

Many observers ascribe much of the relatively low agricultural productivity in Africa south of the Sahara (SSA) to African farmers' limited use of fertilizers (Gregory and Bumb 2006; Kelly 2006; Morris, Kopicki, and Byerlee 2007). SSA farmers apply only 9 kilograms (kg) of fertilizer per hectare (ha), on average, compared with 73 in Latin America and 100 to 135 in Asia, where as much as 50 percent of the Green Revolution yield growth is attributed to fertilizer use (IFDC 2006). Low fertilizer application rates among SSA farmers are often attributed to problems associated with thin markets as well as weak infrastructure and institutions that impede fertilizer distribution and demand in spite of its expected profitability (Omamo et al. 2001; Kherallah et al. 2000; Jayne et al. 2003; Gregory and Bumb 2006; Poulton, Kydd, and Doward 2006). In response, several African heads of state committed to fertilizer subsidies in the 2006 Abuja Declaration on Fertilizer for an African Green Revolution, and especially after the 2007/2008 food price crisis (Jayne and Rashid 2013; Kelly, Crawford, and Ricker-Gilbert 2011).

In response to a severe drought in 2004/2005, the government of Malawi implemented a large-scale Farm Input Subsidy Program (FISP) distributing hybrid or improved open-pollinated variety (OPV) seeds and 50 kg of basal fertilizer and 50 kg of urea to targeted recipients, approximately 50 percent of the population. Aggregate maize production doubled in 2006, then tripled in 2007, going from a 43 percent national deficit in 2005 to a 53 percent surplus in 2007 (Denning et al. 2009). In a nation where inhabitants consume approximately 1,193 kilocalories from maize per day and grew maize on approximately 40 percent of cultivated land in 2005 (FAO 2005), the fertilizer subsidy scheme's apparent success in dramatically improving Malawi's food security attracted widespread attention and helped turn fertilizer subsidies into a high-level political issue.

Yet questions linger as to whether low and variable soil fertility, frequent drought, and high fertilizer prices render fertilizer unprofitable for large subpopulations of African farmers, at least in periods of unfavorable weather (Waithaka et al. 2007; Zingore et al. 2007; Marenya and Barrett 2009a, 2009b). The existing literature has thus far failed to offer credible large-scale assessment of the profitability of fertilizer application due to a dearth of experimental data that vary across weather conditions and space. Published studies typically rely on observational data that cannot control effectively for unobserved farmer and location attributes that may jointly affect fertilizer use and output. This shortcoming has sharply limited researchers' ability to make any rigorous, general statement about the expected profitability of fertilizer use at the national scale at which policies are made. Given the considerable sums expended by cash-strapped governments on fertilizer subsidies—starting at US$50 million in 2005/2006 and growing to US$265 million in 2008/2009 in Malawi's case—this evidence gap is striking.

In this study, we use a large-scale, repeated, nationwide experimental, plot-level dataset from Malawi, merged with detailed soil and weather data, to generate flexible maize production function econometric estimates of the marginal physical returns to fertilizer use. Randomized assignment of fertilizer applications managed by nonrandomly selected local farmers combined with detailed agronomic controls enables us to identify the causal effects of fertilizer application on maize yields. Because the sample of farmers included in the nationwide experiments was nonrandom and potentially selected in part based on farming skill or willingness to cooperate with extension agents, however, our estimates are not of nationwide average expected returns, which would require a random sample of farmers as well as randomized application of fertilizer. Rather, these estimates likely represent instead an upper bound on the expected returns to fertilizer use in maize cultivation in Malawi or, alternatively, the expected returns among a large sample of the nation's best farmers.

We then use the estimated maize production function and historical weather and price data to simulate the distribution of the expected profitability of fertilizer use over space in the face of uncertain weather given prevailing retail output and input prices during the subsidy period in Malawi. Finally, we correlate those estimated expected benefits of fertilizer use with local poverty rates so as to establish whether yield gains reasonably attributable to fertilizer accrue primarily in poorer or richer areas of the country. If fertilizer subsidies are to offer a distributionally progressive instrument for reducing widespread poverty among small farmers in SSA, then fertilizer not only needs to increase yields but those gains should ideally also be concentrated in regions of higher initial poverty. If fertilizer subsidies encourage uptake and expand output among all farmers (meaning, is not concentrated among the poorest), this would imply that the poverty reduction effects, if any, of fertilizer subsidies are more likely to result from increased aggregate output inducing agricultural wage and market price effects that benefit poor workers and consumers, as was true of the Green Revolution (David and Otsuka 1994; Evenson and Gollin 2003).

We find that given 2009/2010 maize and fertilizer prices, the fertilizer bundle recommended under Malawi's FISP is almost always and everywhere profitable in expectation. Indeed, fertilizer use would remain profitable in expectation even in the face of significant fertilizer price increases and drought conditions. While the program does appear to favorably affect maize yields and farm profits, however, the spatial pattern of those gains is largely uncorrelated with headcount poverty rates, calling into question the extent to which Malawi's fertilizer subsidies have been pro-poor among farmers.[1]

The remainder of the paper is structured as follows. Section 2 briefly reviews the related background on fertilizer application and Malawi's subsidy program. Section 3 describes our data and provides summary statistics. Section 4 presents the empirical method to calculate the expected returns to fertilizer and expected benefit–cost ratios under different price scenarios and the historical distribution of weather conditions. We also explore the spatial correlation of the expected returns to fertilizer estimates with headcount poverty levels. The results are presented in Section 5. Finally, Section 6 discusses our results and concludes with some policy recommendations.

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[1] We are unable to establish the price, wage, or employment effects, if any, of fertilizer use and thus cannot address the likely poverty effects among nonfarmers.

2. BACKGROUND

While the Green Revolution resulted in a doubling of average yields for staple crops in Asia during the 1960s and 1970s, Africa's agricultural productivity has lagged behind. Several African governments promoted fertilizer use during the 1970s and early 1980s—for example, through direct subsidies, input credit programs, centralized fertilizer procurement and distribution sites—with some success (Denning et al. 2009). However, a general phase-out of input subsidy programs occurred in the 1990s, primarily due to fiscal constraints or inefficiency. Following severe weather events and the 2007/2008 food price crisis, however, several African countries made a commitment to reintroduce yield-increasing policies (Jayne and Rashid 2013; Kelly, Crawford, and Ricker-Gilbert 2011). For example, Malawi suffered a severe drought in 2004/2005, resulting in approximately 4.2 million people, or 38 percent of its population, requiring food aid (Denning et al. 2009). As a result, the government implemented its input subsidy program—FISP. Aggregate maize production doubled in 2006, then tripled in 2007, going from a 43 percent national deficit in 2005 to a 53 percent surplus in 2007 (Denning et al. 2009). In a nation where inhabitants consumed approximately 1,193 kilocalories worth of maize per day and grew maize on approximately 40 percent of cultivated land in 2005 (FAO 2005), the fertilizer subsidy scheme's apparent success in dramatically improving Malawi's food security attracted widespread attention and helped turn fertilizer subsidies into a high-level political issue, not just in Malawi but also throughout Africa.

Despite the Malawi fertilizer program's seeming success, some have criticized its high cost, starting in 2005/2006 at US$50 million, and growing to US$265 million during the 2008/2009 growing season, due in part to soaring global fertilizer prices (Chibwana et al. 2012; Dorward and Chirwa 2011). Others have criticized it as an unwarranted public subsidy of fundamentally private goods.[2] Still others express doubts as to how much of Malawi's recent maize yield gains can be attributed to its fertilizer subsidy program, the introduction of which fortuitously coincided with several years' favorable growing conditions (Ricker-Gilbert et al. 2009). Furthermore, there is some evidence that although subsidies may have increased crop yields, poverty levels have remained the same, raising questions about the program's efficacy in reducing poverty and food insecurity (Chapoto et al. 2011).

Several recent studies have sought to explain the relatively low observed fertilizer adoption rates among smallholder farmers in Africa and the variability in fertilizer use despite high expected payoffs (Duflo et al. 2008, 2011; Marenya and Barrett 2009a, 2009b). Observed and unobserved heterogeneity among both farmer attributes (for example, patience, skill) and soil characteristics affect fertilizer profitability (Foltz et al. 2011). For example, Marenya and Barrett (2009a, 2009b) show that fertilizer yield responses vary with soil organic matter content, making fertilizer application less profitable on poorer quality soils, and that farmer fertilizer application behavior responds accordingly. Furthermore, the returns to fertilizer may be greater when combined with complementary agricultural inputs and practices, such as improved seeds, irrigation, frequent weeding, and so on (Foltz et al. 2011). Finally, highly volatile fertilizer and crop prices cause the profitability of fertilizer application to vary with prices over space and time and may induce risk-averse farmers to forego fertilizer use (Dercon and Christiaensen 2011; Morris et al. 2007).

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[2] See, for example, the comments by the World Bank's chief economist for the Africa Region, Shanta Devarajan, at http://blogs.worldbank.org/africacan/fertilizer-subsidies-in-malawi, and associated responses.

One way in which policymakers have responded to low adoption levels is by subsidizing farmers' fertilizer purchases. Conventional subsidies stimulate demand by lowering the price faced by private buyers, but the gains often accrue disproportionately to suppliers rather than farmers, given relatively price-inelastic supply and price-elastic demand. Nonetheless, several African heads of state signed the Abuja Declaration in 2006, committing to the use of universal subsidies.

In Malawi, small-scale input subsidy programs (for example, the Starter Pack Scheme and Targeted Inputs Program) existed in the early 2000s. Those were scaled up in 2005 under FISP to include approximately 50 percent of farmers in the country. The program distributes vouchers for fertilizer, hybrid or OPV seeds, or pesticides at reduced prices, or some combination thereof. Recipients receive vouchers for one 50 kg bag of basal fertilizer and one 50 kg bag of urea (to cover approximately 0.33 hectare of land).[3] The subsidy covered 64 to 91 percent of the cost of fertilizer between 2005 and 2010. Initially OPV maize seeds were distributed, but they were subsequently replaced predominantly by hybrid maize varieties. In 2007/2008, FISP also distributed cotton and legume seeds, and in 2008/2009 it also distributed tea and coffee fertilizers. Dorward and Chirwa (2011) and Dorward et al. (2008) contain more details on Malawi's FISP. Lunduka et al. (2013) provide a thorough review of studies of FISP's effects on maize production, prices, land allocation decisions, demand for inputs, and household welfare.

The stated goal of fertilizer subsidy programs is often to both reduce poverty and increase production (Kelly, Crawford, and Ricker-Gilbert 2011), but achieving both objectives appears difficult. Targeting better-off farmers may result in higher yields due to their superior access to fertile land, seasonal financing to purchase complementary inputs, skill, and so forth, but subsidizing the better off also results in a higher crowding-out effect of commercial fertilizer (Jayne et al. 2013; Ricker-Gilbert, Jayne, and Chirwa 2011). Furthermore, if the gains from subsidies accrue primarily to better-off farmers, or in better-off regions of the country, then one necessarily relies on national, rather than local, food and labor markets to propagate the gains to the poor (Minten and Barrett 2008). So the spatial pattern of yield gains may matter to the poverty reduction effects of fertilizer subsidy schemes and remains unexplored in the literature.

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[3] The average farm in Malawi is 1.12 ha. Farm sizes tend to be smaller in the south where the population density and poverty levels are higher (Holden and Lunduka 2012).

3. DATA AND SUMMARY STATISTICS

Experimental Field Trails Data

We use on-farm experimental field trial data conducted by the Maize Productivity Task Force in 1995/1996 and again in 1997/1998 after the Ministry of Agriculture called for fertilizer verification trials to determine which fertilizer combinations would be best suited to different soil types throughout Malawi (Snapp et al. 2010; Benson 1999a). Six treatments of different fertilizer bundles were randomly assigned across 1,677 sites nationwide in 1995/1996, while experiments with four of those treatments were repeated on 1,407 sites in 1997/1998, with 1,205 overlapping locations across the two years (Table 3.1). As expected, yields increase with the nitrogen, phosphate, and sulfur contents of a fertilizer application. Interestingly, treatment 5 leads to statistically significantly higher (at the 1 percent level) mean yields than treatment 6, which has a higher nitrogen and phosphate content but no sulfur. Yields in 1995/1996 were statistically significantly higher (at the 1 percent level) than yields in 1997/1998 for each treatment. Farmers selected field sites on which fertilizer had not been applied and that had been fallow for at least two years. The 1997/1998 trials were in the same location as the 1995/1996 trials, but not at the exact same sites, so as to ensure that the preceding treatments did not affect subsequent trial yields (Figure 3.1).[4] Two different maize varieties were used: the shorter-duration hybrid, MH18, was planted at about two-thirds of all sites—those in lowland areas and in rain-shadow areas in the uplands (Sauer and Tschale 2009; Benson 1999a).

Table 3.1 Treatments

Treatment	**Nutrients (kg/ha)**			**Fertilizer**		**Mean yields (kg/ha)**	
	N	***P***	***S***	***Basal (50 kg bags/ha)***	***Top dressing (50 kg bags/ha)***	***1995/1996 trial***	***1997/1998 trial***
1	0	0	0	0	0	1,410	1,124
2	35	0	0	0	1.5 Urea	2,183	-
3	35	10	2	1 x 23:21:0+4S	1 Urea	2,358	1,997
4	69	21	4	2 x 23:21:0+4S	2 Urea	2,882	2,523
5	92	21	4	2 x 23:21:0+4S	3 Urea	3,147	2,915
6	96	40	0	1.75 DAP	3.5 Urea	2,947	-

Source: Maize Productivity Task Force experimental data (Benson 1999a).
Note: kg/ha = kilogram per hectare; DAP = diammonium phosphate; N = nitrogen; P = phosphate; S = sulfur
Differences in mean yields between all treatment combinations are statistically significant at the 1% level except for treatments 2 and 3, which are not statistically significantly different.

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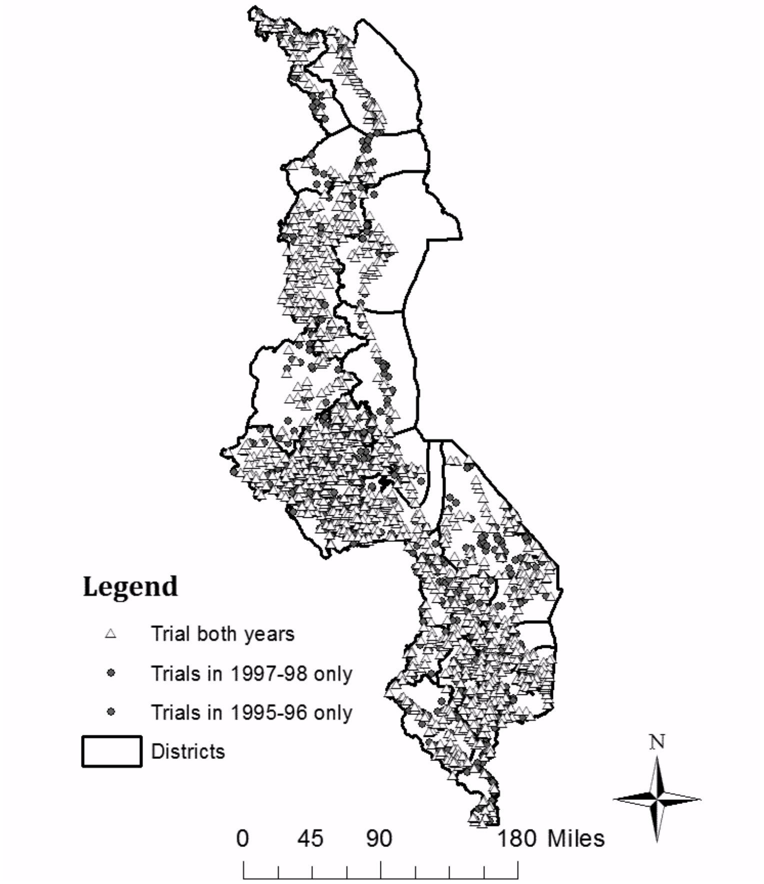
[4] We use *location* to refer to the same geographic area at which one or more *sites* were chosen at which to perform the field experiments. Therefore, up to two different *sites* (one for the 1995/1996 trials and one for the 1997/1998 trials) were chosen at one location.

Figure 3.1 Field trial sites



Source: Maize Productivity Task Force experimental data (Benson 1999a).

Because the goal of the demonstration plots was to introduce new fertilizer recommendations to farmers, representative farmers were chosen to manage the sites. These local farmers were trained by regional field assistants to manage the experiment sites. The field assistant then hosted two field days with local farmers at each site. The first was planned for when the maize was fully grown but still green, and the second occurred after harvest when the grain yield had been weighed. The field assistants collected several types of data, including soil samples, farmer comments, crop growth stage dates, incidence of pest attack, and harvest data (Sauer and Tschale 2009; Benson 1999b).[5] Table 3.2 shows the mean *Striga* and termite infestation by year at each site, as reported by farmers overseeing the plots. Farmers were asked to observe whether the site was infested by *Striga*, differentiating between infestation on less than 50 percent of planting stations (some infestation) or more than 50 percent (high *Striga* infestation). Between 21 and 28 percent (6 to 7 percent) of sites suffered moderate (high) infestation each year. Termites were observed on approximately 40 percent of sites in both years.[6] We have no reason to believe that pest infestation rates are endogenous to the fertilizer treatments.

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[5] Soil samples were collected on a small share of the experimental plots, effectively precluding their use in the estimation below.

[6] Pest infestation is not chronic: the correlation between *Striga* infestation between both years is 0.19; the correlation between high *Striga* infestation is 0.12 between both years; and the correlation between termite infestation is 0.10 between both years.

Table 3.2 Summary statistics: *Striga* and termite infestation

Variable	1995/1996	1997/1998
Striga infested	27.8%	21.0%
High *Striga* infestation	6.4%	6.7%
Termite infested	39.8%	38.8%

Source: Maize Productivity Task Force experimental data (Benson 1999b).

Soil Data

To control for soil heterogeneity that may affect the marginal physical product of fertilizer on maize, we use soil maps generated by the Land Resources Conservation Board at the Ministry of Agriculture in Malawi in collaboration with the Food and Agriculture Organization and the United Nations Development Programme in the 1980s and 1990s (Eschweiler et al. 1991). The maps contain soil characteristics, including soil type, slope, cation exchange capacity (CEC), and soil nitrogen, phosphate, and potassium content. Table 3.3 shows the mean soil characteristics for each site. The terrain is flat (steep) on 48 percent (3 percent) of sites. The soils are on average acidic. Given the proximity in location of the trial plots in both seasons, we can reasonably assume that the sites shared similar agroecological characteristics, although there is surely still unobserved plot-level variation in soil conditions. Nonetheless, we can estimate the marginal impact of fertilizer on maize yields because application rates were randomized across plots, plot management was standardized, and we can control for a host of agronomic conditions that might affect the marginal physical product of fertilizer.

Table 3.3 Summary statistics: Soil characteristics by trial site (from soil map, *n* = 1,891)

Variable	Mean	Standard deviation
Maize variety (D, 1 = MH18)	0.666	0.472
Terrain is flat (D)	0.476	0.500
Terrain is steep (D)	0.026	0.160
Soil is sandy (D)	0.053	0.225
Soil is sandy/clay (D)	0.021	0.144
pH	5.881	0.410
Soil has high cation exchange capacity	0.253	0.435
Soil has high nitrogen content	0.021	0.142
Soil has high phosphate content	0.061	0.239
Soil has high potassium content	0.881	0.324

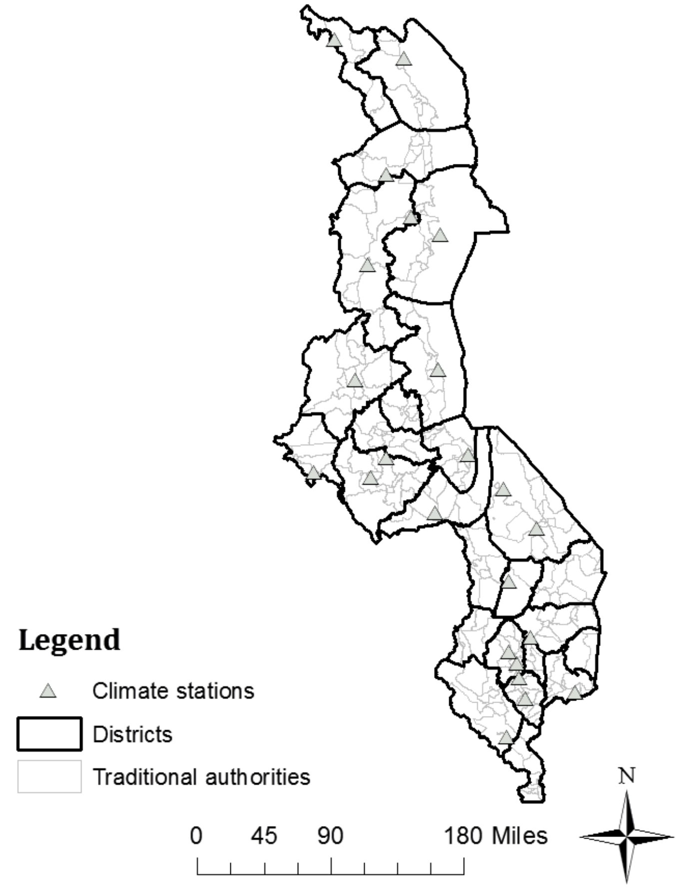
Source: Maize Productivity Task Force experimental data (Benson 1999b); Land Resources Conservation Board Soils Map (Eschweiler ET al.1991).

Note: D = dummy variable.

Climate Controls

We control for weather variability by using daily rainfall and temperature time series data from 23 weather stations distributed throughout Malawi as collected by the Malawi Meteorological Service (Figure 3.2). The first year of available rainfall data differs by district, ranging between 1903 and 1976, and ending in 2009 for all districts. The temperature data also differ in start year, ranging between 1956 and 1984, and ending between 2002 and 2008.

Figure 3.2 Meteorological stations

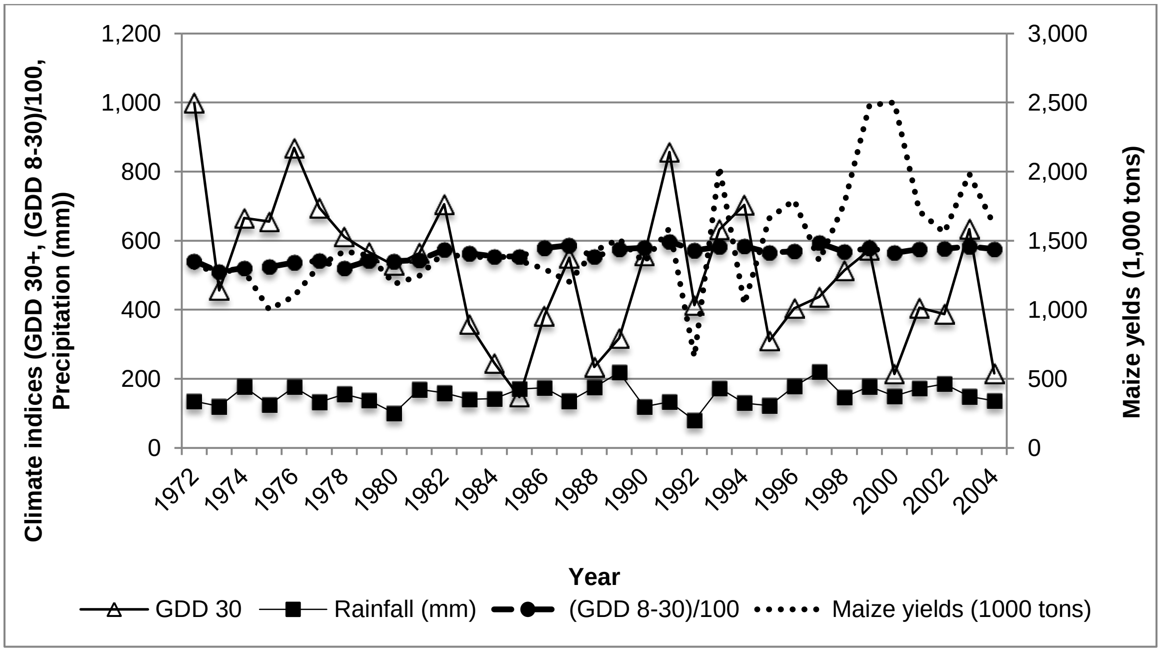


Source: Malawi Meteorological Service (2012).

We build three weather variables to control for temperature and rainfall. First, we calculate the number of growing degree days between 8°C and 30°C (GDD 8–30) between the reported planting and harvest dates to predict maize development rates. Second, we calculate the number of growing degree days above 30°C (GDD 30+) to control for high temperatures that might harm maize growth. Finally, we calculate the total precipitation for the 21-day period centered on the silking date, to control for anthesis—the period when maize flowers and is particularly susceptible to drought. Appendix A includes a more thorough description of the construction of these weather variables. Each experimental field site was linked to the three nearest weather stations, and a single average value was calculated using inverse distance weighting.

Figure 3.3 shows these weather measures from 1972 to 2004. As expected, a high GDD 30+ corresponds with past drought years, notably seasons 1982/1983, 1991/1992, and 1994/1995. Figure 3.3 also includes total maize yields (FAO 2005). Years characterized by high GDD 30+ and low precipitation are, as expected, generally accompanied by low maize yields.

Figure 3.3 Weather and maize yields, 1972–2004



Source: Author's creation based on Malawi Meteorological Service (2012) and FAO (2005).
Note: GDD = growing degree days, mm = millimeter.

Fertilizer and Maize Prices

We calculated district-level median fertilizer prices from the agriculture module data in the third Integrated Household Survey for Malawi (NSO 2012). In the surveys, respondents were asked the quantity and value of unsubsidized fertilizer purchased. Our analysis, therefore, examines the market cost of fertilizer, not the subsidized cost to farmers nor the cost to the government. District-level median maize prices were calculated using the Ministry of Agriculture's monthly maize prices, retail, between December 2009 and March 2010 (the range of dates for which fertilizer prices were reported). Table 3.4 summarizes median maize and fertilizer prices in Malawian kwacha per kg.

Table 3.4 Summary statistics: Prices (kwacha/kg)

Variable	Mean	Standard deviation	Minimum	Maximum
		***n* = 23 districts**		
Maize	46.39	6.68	32.67	63.28
DAP	106.19	10.89	90.00	153.00
NPK	102.32	8.45	80.00	120.00
Urea	97.52	5.28	89.47	110.00

Source: Integrated Household Survey for Malawi (NSO 2012).
Note: kg = kilogram; NPK = nitrogen, phosphorus, and potassium; DAP = diammonium phosphate.

Poverty Maps

Finally, to correlate our spatially explicit estimates of the expected marginal benefit–cost ratio for fertilizer application with local poverty rates, we use the suite of poverty measures reported for each of Malawi’s 28 districts in the 1998 poverty map from CIESIN (2005): mean daily household consumption per capita, the Gini index of consumption inequality, the poverty headcount rate (percentage of the population living below $1.25 per capita/day in purchasing power parity), the poverty gap, the poverty severity index, maximum education level attained, and the travel time to the nearest market per enumeration area. These estimates were generated using standard poverty mapping methods (Elbers, Lanjouw, and Lanjouw 2003). We use poverty maps from 1998 as those are the closest to when the field trial data were collected.

4. METHODS

We first estimate a production function with the experimental data described above, following methods used in other econometric studies of fertilizer's site-specific impact on maize yields (for example, Babcock and Pautsch 1998; Anselin, Bongiovanni, and Lowenberg-DeBoer 2004; Liu, Swinton, and Miller 2006). In particular, we estimate a generalized quadratic production function of the form

$$y_{kit} = \alpha_0 + \sum_w \alpha_w x_{kitw} + \sum_w \sum_v \beta_{wv} x_{kitw} x_{kitv} + \eta_i + \delta_t + \varepsilon_{kit}, \qquad (1)$$

where y_{kit} represents the yield for treatment *k* on site *i* in year *t;* x_{kitw} and x_{kitv} represent all variables (indexed by *w and v*, respectively) potentially affecting yields: nutrient amounts in the fertilizer, soil characteristics, temperature and rainfall; η_i is a site-level random effect; δ_t is a year-specific fixed effect; and ε_{kit} represents the independent and identically distributed mean zero, regression error. α_0, α_w, and β_{wv} are the parameters of interest. More specifically, we control for site-specific field characteristics, that is, whether the site was infested by *Striga* or termites, as well as site-level soil quality characteristics extracted from national soil maps, that is, the slope, soil texture, pH, CEC, nitrogen, phosphate, and potassium content, and weather. We control for year/season-specific effects by including a dummy variable for the 1995/1996 observations.[7] The data do not include observations for any inputs that were not controlled experimentally, so we cannot control for factors such as labor applications per plot. We must therefore assume that farmers optimally apply labor so that the marginal returns estimates for fertilizer include the associated induced changes in labor allocation, not merely the biochemical effects of the nutrient amendments. We correct for heteroskedasticity and spatial autocorrelation by clustering standard errors at the site level.[8]

The nutrients applied to the field trial sites are as explained above: nitrogen, sulfur, and phosphate. In subhumid environments like Malawi, nitrogen is known to be the main driver of cereal yield response in soils with low organic matter. However, applying only nitrogen as fertilizer (in the form of urea) can lead to sulfur and phosphate deficiencies in the longer term (van der Velde et al. 2013). Potassium is less deficient in Malawian soils except perhaps for the intensive cultivation of tobacco. Zinc and other micronutrients also contribute to soil fertility but are rarely deficient except perhaps in small, localized areas of Malawi (Benson 1999a, 1999b). Chilimba and Liwimbi (2008) do conclude, however, that generally a basal dressing including zinc or potassium, or both, is superior to a basal application without them.

Although both sulfur and phosphate are known to contribute to maize yields, we cannot control for both because there is insufficient variation between treatments. Because sulfur more consistently showed yield responses than phosphate in the field trials, NPK 23:21:0+4S (N = nitrogen; P = phosphate; K = potassium; S = sulfur) was promoted as the basal dressing in Malawi's FISP. We therefore choose to control for nitrogen and sulfur in the production function estimation.

Given the estimated maize production function, we can compute the expected marginal physical returns to fertilizer, $E[dy]$, which equals the sum of the marginal products of each element in the fertilizer bundle, nitrogen and sulfur, multiplied by the percentage of the nutrients in the specific fertilizer:

$$E[dy] = \gamma_n \frac{\partial y}{\partial n} dn + \gamma_s \frac{\partial y}{\partial s} ds. \qquad (2)$$

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[7] The panel data are unbalanced, but the field trial site selection was random and therefore the remaining unobservables should be uncorrelated with the regressors so that we estimate a random-effects model.

[8] A Breusch-Pagan/Cook-Weisberg test rejects the null hypothesis that all conditional variances are equal.

For example, NPK (23:21:0+4S) contains 23 percent N, 21 percent P, 0 percent potassium, and 4 percent S, so γ_n= 23 percent and γ_s= 4 percent, while urea contains 46 percent N so that γ_n= 46 percent and γ_s= 0 percent. Given the estimation results from equation (1), the expected marginal return to fertilizer f is

$$E[dy] = \gamma_n(\alpha_n + \Sigma_v \beta_{nv} x_{kitv}) + \gamma_s(\alpha_s + \Sigma_v \beta_{sv} x_{kitv}). \qquad (3)$$

Using historic district-level weather data along with the regression results, we estimate the distribution of expected returns for the FISP bundle, NPK and urea, at each site for each available year. We calculate the growing degree days above 30°C (GDD 30+), GDD from 8°C to 30°C (GDD 8–30), and rainfall (in millimeters) weather variables for each year for each site by using the silking, planting, and harvest dates from the 1995/1996 field trials (Lobell et al. 2011). We use the joint distribution of the observed weather variables to simulate the expected returns for each available year for the trial sites. The availability of data varies by trial site and ranges between a start date of 1971 and an end date of 2004.[9] We have to assume that soil characteristics remain constant as we do not have annual soil characteristics.

Given the distribution of expected returns of fertilizer and fertilizer and maize prices, we then estimate the expected benefit–cost (EBC) ratios and the probability that fertilizer is profitable for a given plot. While weather conditions may affect maize prices and, to a lesser degree, fertilizer prices, data limitations keep us from controlling for the variation in prices over time. We therefore use district-level median maize and fertilizer prices from the third Integrated Household Survey data for Malawi from 2009/2010 (Malawi, NSO 2012), a year during which FISP was in effect. The expected profit, $E[\pi]$, from fertilizer application is

$$E[\pi] = E\left[\Delta y \cdot p_y\right] - \Delta f \cdot p_f, \qquad (4)$$

where p_y is the price of maize and p_f is the price of fertilizer, the first of which is unknown when farmers make fertilizer purchase decisions and therefore is subject to uncertainty—hence the expectations operator.[10] The price of fertilizer, however, is known at the time of purchase. Δy_f represents the change in yields resulting from different input applications. Here, we estimate the change in yields between applying the FISP bundle (50 kg urea + 50 kg NPK) relative to applying no fertilizer—Δf. From the standard first-order conditions of the risk-neutral producer's profit-maximizing problem, fertilizer application will be profitable in expectation so long as $E[\pi] > 0$, which constitutes a necessary condition for fertilizer application.[11]

Finally, we correlate the entire set of simulated EBC ratios by district with the 1998 poverty map (Malawi, NSO 2012) using multiple poverty measures (mean daily household consumption per capita, the Gini index of consumption inequality, the poverty headcount rate [percentage of the population living below $1.25 per capita/day in purchasing power parity terms]), the poverty gap, the poverty severity index, maximum education level attained, and the travel time to the nearest market per enumeration area). These estimates were generated using standard poverty-mapping methods (CIESIN 2005). The number of observations per district varies between 44 and 3,439.

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[9] Because we match each trial site to three stations, we use the set of years available at each of the three stations per site.

[10] Lacking data with which to establish the joint distribution of maize prices and the marginal physical product of fertilizer, we must assume these are statistically independent, thus $E\left[dy \cdot p_y\right] = E\left[dy\right] \cdot E[p_y]$.

[11] This is not a sufficient condition because risk aversion, liquidity constraints that force the farmer to borrow funds at a positive interest rate in order to purchase fertilizer, and other factors can still make fertilizer use unattractive even with $E[\pi] > 0$.

5. RESULTS

Maize Production Function Estimation

The full regression estimation results of the maize production function, equation (1), are reported in column 1 of Table A.1 in the appendix. Because we are interested in the marginal effects of fertilizer, we demean the data both to make the generalized quadratic an exact second-order approximation of the unknown true production function and to make the interpretation of the coefficients more straightforward.

As expected, nitrogen and sulfur each have a statistically significant positive effect on yield that diminishes with the application rate. The interaction of nitrogen with sulfur is also statistically significantly positive, indicating that each is limiting, leading to complementarities in combining the two nutrients. The estimated marginal yield effect of nitrogen fertilizer also varies statistically significantly with weather, increasing (decreasing) with precipitation (high temperatures, reflected in GDD 30+). Likewise, the marginal yield effects of sulfur vary statistically significantly with soil phosphate content and slope. The clear implication is that the marginal returns to fertilizer vary predictably across growing seasons and over space, so that any benefits of Malawi's subsidy program will necessarily be heterogeneous. The key questions are how big those benefits are, how unevenly they are spread, and whether that variation is distributionally progressive (regressive). That is, are the expected marginal gains to additional fertilizer application positively (negatively) correlated with poverty headcount rates?

The coefficient estimates on the other control variables are as one would expect. The regression estimates also indicate that yields in the 1995/1996 season were higher. Independently, GDD 8–30 and rainfall both have a positive, albeit statistically insignificant, effect on yields, while GDD 30+ has a negative and significant effect. Yields were higher with the shorter-stature MH18 hybrid variety and in higher pH soils, since most of Malawi's farmland is moderately to mildly acidic. High levels of *Striga* and termite infestation and steeply sloped sandy soils are associated with lower yields. With an overall R^2 of 0.34 with nearly 11,000 observations, the regression does a reasonably good job of explaining variation in maize yields. We have no reason to expect a significant change in the production function over a short time, especially over the course of the field trial sites (1995/1996 and 1997/1998) and FISP (2005–). However, there may be slight differences due to the different seed varieties distributed under FISP (hybrid, OPV) relative to those used in the field experiments (M17, M18). Although using these somewhat dated data to measure the production function is not ideal, it is the most accurate feasible estimation of these parameters we are aware of for Malawi, or any African country, at nationwide scale.

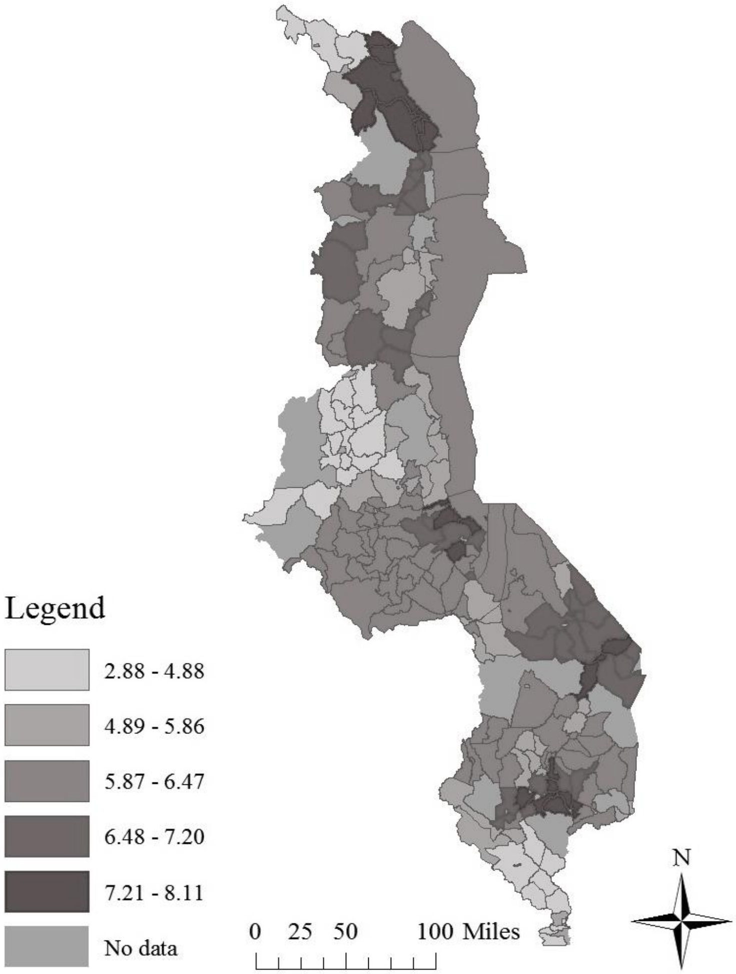
We ran robustness checks on these estimates using both a Hausman-Taylor estimator (model II in Appendix Table A.1), which allows some of the regressors to be correlated with the unobserved individual effect, η_i, and a random effects model estimated only on the balanced panel subset of data observed in both years (model III). The results are generally quite consistent across specifications, especially as regards the central parameters of interest relating to the estimated marginal effects of fertilizer application on maize output. The sign of the estimated effect differs only for the second-order effects of pH where it is negative (as expected) for model I but positive in models II and III.

Based on the estimated maize production function, we compute the expected marginal physical returns to fertilizer following equation (2). We find expected marginal returns of 25.2 kg maize per kg nitrogen for the FISP bundle when the fertilizer application rate is zero and applied in conjunction with hybrid seeds. The expected marginal returns decrease to 23.2 kg (21.1 kg) maize per kg nitrogen when the fertilizer application rate increases to 10 (20) kg nitrogen, which falls within the wide range of maize responses to fertilizer found in the literature, which typically range between 8 kg and 24 kg maize per kg nitrogen applied (Jayne and Rashid 2013), depending in part on the underlying quantity of fertilizer applied at which the marginal products are evaluated.

Profitability of the FISP Bundle

Given 2009/2010 maize and fertilizer prices and our estimated maize production function, we find that the fertilizer bundle recommended under Malawi's FISP is almost always and everywhere profitable in expectation, at least when applied with hybrid seeds by farmers comparable with those in the sample. Maps of the profitability expressed in EBC ratio terms offer strong indications as to where the gains from fertilizer use induced by subsidies are concentrated: in the northern region of Karonga and the west of the country (Figure 5.1).

Figure 5.1 Expected benefit–cost ratio of FISP bundle



Source: Maize Productive Task Force (Benson 1999b); Malawi Meteorological Service (2012); Integrated Household Survey for Malawi (Malawi, NSO 2012); Land Resources Conservation Board Soils Map (Eschweiler et al. 1991).

Note: FISP = Farmer Input Subsidy Program.

We compare the FISP bundle with fertilizer applications made up uniquely of urea and NPK of the equivalent value as the FISP bundle, that is, 97 kg NPK and 103.2 kg urea, the equivalent to 100 kg of the FISP bundle in monetary value (Table 5.1). While we find that the EBC ratio of urea is higher than that of NPK and the FISP bundle, had the experimental design allowed us to control for phosphate, the EBC ratio for NPK might be higher, as we must implicitly put zero value on phosphate since sulfur appears more limiting and the experimental design unfortunately rendered them perfectly collinear. Furthermore, while the application of urea may increase yields in the short term, it may lead to the depletion of other nutrients in the longer term (van der Velde et al. 2013). The three last columns of Table 5.1 show that the expected mean return of urea, NPK, the FISP bundle, and nitrogen for the entire set of simulated data are close to the in-sample means (columns 2, 3 and 4).

Table 5.1 Expected benefit–cost ratios and expected probability of profitability for 97 kg/ha NPK (23:21:0+4S), the FISP bundle (50kg/ha urea and 50kg/ha NPK), and 103.2 kg/ha urea

Indicator	**In-sample**			**Full weather distribution**		
Expected benefit–cost ratio	**FISP**	**NPK**	**Urea**	**FISP**	**NPK**	**Urea**
Mean	4.120	2.154	4.384	4.051	2.125	4.259
Median	4.140	2.156	4.400	4.110	2.156	4.342
Standard deviation	0.584	0.471	0.628	0.702	0.519	0.873
Probability of profitability	1.000	0.981	1.000	0.998	0.962	0.990
n		2,763			34,885	

Source: Maize Productive Task Force (Benson 1999b); Malawi Meteorological Service (2012); Integrated Household Survey for Malawi (Malawi, NSO 2012); Land Resources Conservation Board Soils Map (Eschweiler et al. 1991).

Note: kg/ha = kilogram per hectare; NPK = Nitrogen, Phosphorus, and Potassium; S = Sulfur; FISP = Farmer Input Subsidy Program.

We examine how the expected probability of profitability and benefit–cost ratios might vary with changing fertilizer and maize prices, which are notoriously volatile.[12] Holding maize prices fixed, we first increase the price of the fertilizer for the treatment bundle by 50, 100, 200, and 500 percent (Table 5.2). The expected profitability of fertilizer application is robust to increases in fertilizer prices up to 200 percent. But fertilizer use becomes widely—but not everywhere—unprofitable with fertilizer price increases of 500 percent, as occurred between 2004 and 2008. Similarly, we estimate the expected probability of profitability and EBC ratios when maize prices decrease, holding fertilizer prices at 2009/2010 levels. Even with a 50 percent decrease in the price of maize, the probability of profitability remains high at 0.998 and the EBC ratio decreases only to 2.025 (Table 5.2).

Table 5.2 Expected probability of profitability and expected benefit–cost ratio with 50 to 500% fertilizer price increases and 25 to 50% maize price decreases from 2009/2010 prices

Indicator	**FISP expected benefit–cost ratio**			**FISP probability of profitability**
	(*n* = 34,885)			
Fertilizer price increase:	***Mean***	***Median***	***Standard deviation***	***Mean***
50%	2.701	2.740	0.468	0.994
100%	2.025	2.055	0.351	0.988
200%	1.350	1.370	0.234	0.936
500%	0.675	0.685	0.117	0.123
Maize price decrease:				
25%	3.038	3.082	0.527	0.996
50%	2.025	2.055	0.351	0.988

Source: Maize Productive Task Force (Benson 1999b); Malawi Meteorological Service (2012); Integrated Household Survey for Malawi (Malawi, NSO 2012); Land Resources Conservation Board Soils Map (Eschweiler et al. 1991).

Note: FISP = Farmer Input Subsidy Program.

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[12] For example, international DAP and urea prices increased roughly sixfold from 2004 to 2008 before retreating sharply by 2009/2010 and settling at roughly two to three times the 2004 prices by 2012/2013 (http://www.africafertilizer.org/Data-Centre/Monthly-International-Prices-for-Fertilizers.aspx).

We also compare how EBC and the probability of expected profitability of fertilizer application vary with changing weather conditions. We compare results estimated for a drought year, 1991, and for a year with favorable rainfall and temperatures, 1984. The likelihood of profitability of the FISP bundle decreases only to 97.3 percent in a drought year. The expected profitability of fertilizer irrespective of growing conditions is a striking result. EBC ratios are greater than 3 in all cases (Table 5.3). These high expected returns to fertilizer help explain the high observed fertilizer application rates recently observed in Malawi where approximately 77.3 percent of maize farmers used an average of 189 kg/ha of fertilizer (calculated using Malawi's 2009 Integrated Survey on Agriculture).

Table 5.3 Expected probability of profitability and expected benefit–cost ratio for a drought year (1991 conditions) and a favorable growing year for maize (1984 conditions)

Indicator		**1984**			**1991**	
Expected benefit–cost ratio	**FISP**	**NPK**	**Urea**	**FISP**	**NPK**	**Urea**
Mean	4.183	2.185	4.474	3.774	2.022	3.816
Median	4.145	2.165	4.411	3.947	2.104	4.041
Standard Deviation	0.619	0.481	0.676	0.950	0.593	1.347
Probability of profitability						
Mean	1.000	0.977	1.000	0.973	0.936	0.955
n		1309			1301	

Source: Maize Productive Task Force (Benson 1999b); Malawi Meteorological Service (2012); Integrated Household Survey for Malawi (Malawi, NSO 2012); Land Resources Conservation Board Soils Map (Eschweiler et al. 1991).

Note: FISP = Farmer Input Subsidy Program.

Poverty

Although FISP does appear to favorably affect maize yields and farm profitability, on average, we find that the spatial pattern of those gains is largely uncorrelated with headcount poverty rates, calling into question the extent to which Malawi's fertilizer subsidies are distributionally progressive across space among farmers. The expected gains from increased fertilizer use do not appear concentrated in regions populated by more poor farmers.

Table 5.4 shows the correlation coefficients between the EBC of a FISP fertilizer ration and various poverty measures. The mean correlation between FISP EBC and the headcount poverty rate is 0.0309 over the entire dataset (*n* = 28,751), statistically significantly different from zero at the 1 percent level but very small in magnitude. These very slightly positive correlations indicate that regions with higher poverty levels are very weakly associated with higher expected fertilizer returns, making the benefits of fertilizer subsidies essentially spatially neutral in the distribution of gains among farmers. Nevertheless, the values are negative for many districts (Figure 5.2), indicating that higher (lower) poverty levels are associated with lower (higher) returns in some parts of Malawi. The districts of Balaka and Mchinji display high positive estimated correlations between poverty rates and expected marginal returns to fertilizer, while other districts, such as Ntcheu and Thyolo, exhibit large negative estimated correlations. The results are generally consistent for other poverty measures—such as mean daily household per capita income, poverty gap, and education levels—and when uniquely isolating the profitability in 1998, the year for which the poverty map was estimated (Table 5.4).

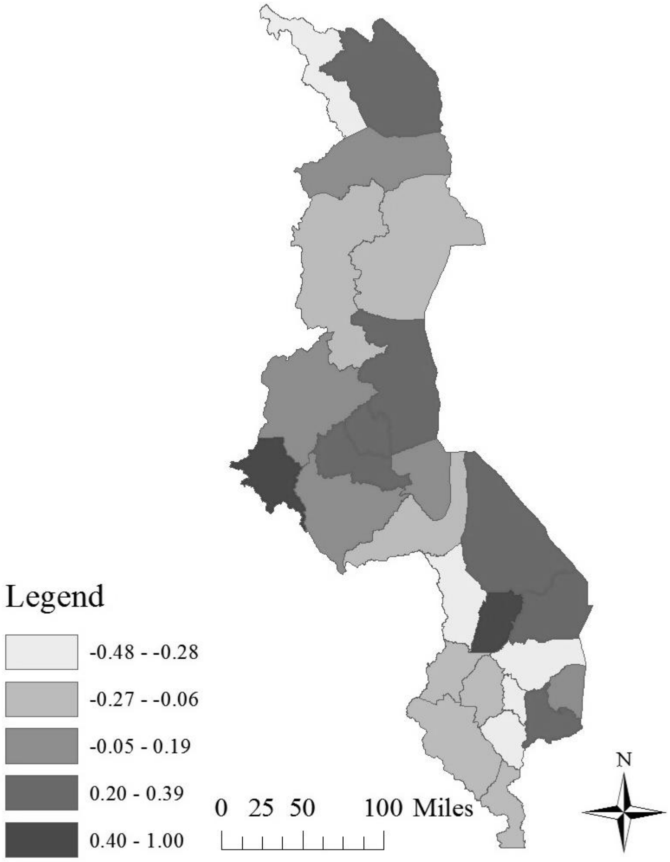
Table 5.4 Correlation coefficients between poverty indices and the expected benefit–cost ratio for fertilizer bundles

	FISP bundle		NPK		Urea	
Indices	**All years**	**1998**	**All years**	**1998**	**All years**	**1998**
Household consumption	0.0043	0.0271	0.0003	0.0125	0.0068	0.0394
Gini index	0.0706***	0.1686***	0.0862***	0.1324***	0.0397***	0.1627***
Poverty headcount	0.0309***	-0.0348	0.0835***	0.0565*	0.0149**	-0.0853***
Poverty gap	0.0324***	-0.0031	0.0958***	0.0900***	0.0036	-0.0644**
Poverty severity index	0.0284***	0.0099	0.0964***	0.1019***	-0.0057	-0.0541*
Travel time to nearest market center	-0.0097*	-0.0465	-0.0955***	-0.1072***	0.0375***	-0.0111
Max education	0.0974***	0.1165***	0.1097***	0.0964***	0.1288***	0.1967***
n	32,692	1,217	32,692	1,217	32,692	1,217

Source: Maize Productive Task Force (Benson 1999b); Malawi Meteorological Service (2012); Integrated Household Survey for Malawi (Malawi, NSO 2012); Land Resources Conservation Board Soils Map (Eschweiler et al. 1991).

Note: FISP = Farmer Input Subsidy Program.

Figure 5.2 Correlation coefficients between poverty headcount rates and FISP expected benefit–cost ratio



Source: Maize Productive Task Force (Benson 1999b); Malawi Meteorological Service (2012); Integrated Household Survey for Malawi (Malawi, NSO 2012); Land Resources Conservation Board Soils Map (Eschweiler et al. 1991).

Note: FISP = Farmer Input Subsidy Program.

6. DISCUSSION

Our results indicate that when optimally applied (that is, with improved seeds, at the right time, and in the correct quantity), the fertilizer bundle distributed under Malawi's FISP—50 kg NPK (23:21:0+4S) and 50 kg urea—appears profitable in expectation for this large sample of farmers, across years with strikingly different growing conditions, and across subregions with markedly different soils and other attributes. Even if fertilizer prices were to rise by as much as 200 percent or maize prices fall by half, the EBC ratio would still exceed 1.

However, our estimated EBC ratios likely represent an upper bound for a few reasons. First, although farmers managed the plots on which the maize fertilizer trials were conducted, farmers were not randomly selected—the extension agents who recruited participants may have selected farmers with greater ability than the average representative farmer. Furthermore, farmers may have made a greater effort to manage the experimental plots knowing that they were participating in a study and being followed by an extension agent. Nevertheless, farmers were selected who had wealth levels similar to those of surrounding farmers. Second, land constraints make fallowing uncommon in Malawi. The sites selected had been left fallow for at least two years, likely making those soils more fertile, with higher organic matter content, than continuously cultivated plots. Finally, our results estimate the returns to fertilizer application rates conditional on the use of improved seeds, which are expected to be higher than fertilizer application used in conjunction with unimproved seed.

Our results also show that the expected benefits of fertilizer use vary significantly across space, and not always in ways that concentrate the gains to farmers from increased fertilizer use in the poorest regions. Fertilizer subsidy programs are often motivated by governments' objective to reduce poverty and food insecurity, especially among smallholder farmers. But if poorer farmers live in areas where growing conditions are less favorable or cultivate soils that do not respond as well to fertilizers as do those of better-off farmers, subsidies might not be a distributionally progressive instrument for poverty reduction, at least not within the subpopulation of farmers (Kelly, Crawford, and Ricker-Gilbert 2011; Marenya and Barrett 2009a, 2009b). Furthermore, there may be trade-offs between targeting poor farmers to generate direct income gains among that subpopulation versus targeting better-off farmers who typically produce greater yields and might thereby generate greater aggregate supply gains that may generate agricultural wage increases or price reductions that benefit poor workers and consumers, respectively, effects we cannot take into account.

We know of no prior published evidence on how the spatial patterns of the expected returns to fertilizer correlate with the spatial distribution of poverty. We find a very mildly positive overall correlation between location-specific estimated poverty headcount rates and expected returns to fertilizer, leaving it unclear whether fertilizer subsidies really are pro-poor and distributionally progressive among growers. Geographic targeting of poor regions with high expected marginal returns could ensure that a government's subsidy program is pro-poor (Lang, Barrett, and Naschold 2012), not only concentrating gains in the poorest areas but also prospectively reducing the potential crowding out effect of fertilizer subsidies on commercial input markets (Jayne et al. 2013; Ricker-Gilbert, Jayne, and Chirwa 2011). Furthermore, targeting the poor who otherwise might not purchase their own fertilizer would give them the opportunity to learn about the benefits of fertilizer application (for example, which fertilizer to apply and how and when to apply it), increasing their likelihood of continued fertilizer use.

The sustainability of fertilizer subsidy programs remains precarious due to high associated costs and heavy logistical demands. Alternative programs—such as constructing roads or investing in agricultural research and design and education programs—could perhaps help alleviate poverty even more effectively (Jayne et al. 2013). Targeting regions with soils that respond especially strongly to fertilizer application and that are populated by the poorest farmers can help increase the efficiency of the program and reduce costs while more effectively promoting its goals of poverty reduction and increasing food security. However, given the high expected profitability of fertilizer used in conjunction with improved seeds, still more work is needed to better understand reasons for low observed fertilizer use and whether a fertilizer subsidy is the optimal tool to address these constraints.

APPENDIX A: SUPPLEMENTARY TABLE

Table A.1 Quadratic production function estimates

Variable	1. RE	2. H-T	3. RE (balanced panel only)	4. Treatment dummies
Year (D, 1 = 95-96)	324.869**	335.770**	332.020**	325.25**
	(41.763)	(19.001)	(44.18)	(41.741)
N fertilizer	16.968**	16.963**	17.021**	
	(0.372)	(0.505)	(0.45)	
S fertilizer	25.294**	25.488**	28.197**	
	(6.543)	(9.51)	(7.911)	
Growing degree days (8°–30°C)	0.004	0.009**	0.005	0.003
	(0.004)	(0.002)	(0.004)	(0.004)
Growing degree days (+30°C)	-0.213**	-0.246**	-0.219**	-0.203**
	(0.067)	(0.051)	(0.071)	(0.068)
Precipitation	0.198	0.175	0.307	0.209
	(0.387)	(0.174)	(0.408)	(0.387)
pH	280.531**	281.391**	301.756**	276.573**
	(61.358)	(108.381)	(66.65)	(61.356)
Striga infested (D)	-117.528	-86.966**	-111.992	-119.736*
	(60.723)	(32.854)	(64.861)	(60.874)
Striga infested (high) (D)	-553.691**	-520.318**	-554.825**	-553.781**
	(94.458)	(53.242)	(101.714)	(94.841)
Termite infested (D)	-250.248**	-296.476**	-268.971**	-249.066**
	(51.31)	(25.625)	(54.706)	(51.359)
Maize variety (D, 1 = MH18)	248.376**	537.560**	237.786**	245.65**
	(53.471)	(123.561)	(60.106)	(53.390)
Terrain is flat (D)	96.284*	210.791	140.251**	93.743*
	(43.059)	(229.628)	(49.034)	(43.123)
Terrain is steep (D)	-328.210**	768.841	-255.978	-333.197**
	(112.027)	(584.683)	(135.511)	(111.817)
Soil is sandy	-305.931**	-960.572*	-316.540**	-305.254**
	(93.814)	(479.204)	(104.356)	(93.699)
Soil is sandy/clay	-491.878**	-933.141	-520.000**	-490.025**
	(156.995)	(784.6)	(187.215)	(157.324)
Squared: N fertilizer	-0.103**	-0.103**	-0.096**	
	(0.008)	(0.011)	(0.009)	
Squared: S fertilizer	-35.856**	-35.934**	-35.773**	
	(3.968)	(6.236)	(4.589)	
Squared: precipitation	0	0.002	0.001	0
	(0.004)	(0.002)	(0.004)	(0.004)
Squared: pH	-12.381	-1.359	26.555	-17.564
	(58.593)	(115.669)	(61.681)	(58.62)

Table A.1 Continued

Variable	1. RE	2. H-T	3. RE (balanced panel only)	4. Treatment dummies
Interaction: GDD 8–30, pH	0.019*	0.018**	0.018*	0.018*
	(0.008)	(0.004)	(0.009)	(0.008)
Interaction: GDD 30+, pH	-0.017	-0.021	-0.004	-0.008
	(0.086)	(0.048)	(0.089)	(0.086)
Interaction: precipitation, S	-0.051	-0.06	-0.007	
	(0.092)	(0.083)	(0.12)	
Interaction: precipitation, pH	-0.562	-0.478	-0.484	-0.59
	(0.998)	(0.408)	(1.048)	(1.006)
Interaction: precipitation, N	0.009*	0.009*	0.011	
	(0.005)	(0.004)	(0.006)	
Interaction: N, S fertilizers	1.260**	1.263**	1.303**	
	(0.197)	(0.282)	(0.237)	
Interaction: N, pH	0.464	0.465	0.544	
	(0.564)	(0.557)	(0.666)	
Interaction: pH, S	-4.119	-4.138	-3.96	
	(12.186)	(11.775)	(14.759)	
Interaction: GDD 30+, S	0.01	0.014	0.008	
	(0.015)	(0.015)	(0.019)	
Interaction: GDD 30+, N	-0.004**	-0.004**	-0.004**	
	(0.001)	(0.001)	(0.001)	
Interaction: S, flat terrain	-20.247*	-20.025**	-28.733**	
	(8.479)	(7.73)	(10.374)	
Interaction: S, steep terrain	-47.847**	-49.589*	-62.948*	
	(18.549)	(22.473)	(24.487)	
Interaction: S, sandy soil	-30.192	-29.464	-47.270*	
	(16.625)	(15.733)	(20.092)	
Interaction: S, sandy/clay soil	38.9	38.693	24.974	
	(23.982)	(25.579)	(30.427)	
Interaction: S, high CEC	-10.723	-10.393	-14.103	
	(10.296)	(9.499)	(12.82)	
Interaction: S, high N	-19.246	-20.367	-10.227	
	(22.805)	(23.305)	(29.127)	
Interaction: S, high P	-46.513**	-47.623**	-58.273**	
	(16.571)	(14.983)	(20.632)	

Table A.1 Continued

Variable	1. RE	2. H-T	3. RE (balanced panel only)	4. Treatment dummies
Interaction: S, high K	-0.776	-1.629	-9.749	
	(13.275)	(12.04)	(15.697)	
Treatment: 96N:40P:0S				1479.832**
				(23.659)
Treatment: 35N:0P:0S				762.59**
				(18.255)
Treatment: 35N:10P:2S				903.761**
				(14.228)
Treatment: 69N:21P:4S				1426.976**
				(17.197)
Treatment: 92N:21P:4S				1744.425**
				(19.993)
Interaction: GDD 8–30, 96N:40P:0S				0.001
				(0.004)
Interaction: GDD 30+, 96N:40P:0S				-0.406**
				(0.083)
Interaction: precipitation, 96N:40P:0S				0.932
				(0.487)
Interaction: pH, 96N:40P:0S				47.782
				(60.276)
Interaction: GDD 8–30, 35N:0P:0S				-0.009**
				(0.003)
Interaction: GDD 30+, 35N:0P:0S				-0.04
				(0.069)
Interaction: GDD precipitation, 35N:0P:0S				0.001
				(0.387)
Interaction: pH, 35N:0P:0S				47.787
				(50.336)
Interaction: GDD 8–30, 35N:10P:2S				0.001
				(0.002)

Table A.1 Continued

Variable	1. RE	2. H-T	3. RE (balanced panel only)	4. Treatment dummies
Interaction: GDD 30+, 35N:10P:2S				-0.163**
				(0.030)
Interaction: precipitation, 35N:10P:2S				0.262
				(0.207)
Interaction: pH, 35N:10P:2S				25.424
				-36.128
Interaction: GDD 8–30, 69N:21P:4S				0.005*
				(0.002)
Interaction: GDD 30+, 69N:21P:4S				-0.273**
				(0.037)
Interaction: precipitation, 69N:21P:4S				0.37
				(0.251)
Interaction: pH, 69N:21P:4S				-12.619
				(43.691)
Interaction: GDD 8–30, 92N:21P:4S				0.006*
				(0.003)
Interaction: GDD 30+, 92N:21P:4S				-0.369**
				(0.042)
Interaction: precipitation, 92N:21P:4S				0.498
				(0.3)
Interaction: pH, 92N:21P:4S				36.305
				(49.953)
Constant	220.285**	208.943**	173.224**	28.508
	-30.431	-38.303	-34.734	-27.3
Within R^2	0.52	.	0.49	0.52
Between R^2	0.1	.	0.12	0.1
Overall R^2	0.34	.	0.35	0.34
N	10,992	10,992	8,000	10,992

Source: Maize Productive Task Force (Benson 1999b); Malawi Meteorological Service (2012); Integrated Household Survey for Malawi (Malawi, NSO 2012); Land Resources Conservation Board Soils Map (Eschweiler et al. 1991).

Notes: RE = random effects; H-T = Hausman-Taylor; CEC = cation exchange capacity; GDD = growing degree days; K = potassium; N = nitrogen; P = phosphate; S = sulfur; D = dummy variable. * $p < 0.05$, ** $p < 0.01$. The dependent variable is yield (kg/ha). Model 1 uses an RE specification, model 2 uses an H-T specification, model 3 uses a random effects specification on the subset of sites with data from both seasons. We demean the data both to make the generalized quadratic an exact second-order approximation of the unknown true production function at the sample mean and to make the interpretation of the coefficients more straightforward.

APPENDIX B: CONSTRUCTION OF THE WEATHER VARIABLES, FOLLOWING LOBELL ET AL. (2011)

First, we calculate the number of growing degree days between 8°C and 30°C (GDD 8–30) between the reported planting and harvest dates to predict maize development rates. Second, we calculate the number of growing degree days above 30°C (GDD 30+) to control for high temperatures that might harm maize growth. Finally, we calculate the total precipitation for the 21-day period centered on the silking date, to control for anthesis—the period of time during which a flower is open and functional and most susceptible to drought. Growing degree days were calculated at each field trial site as

$$GDD_{base,opt} = \sum_{t=1}^{N} DD_t \qquad DD = \begin{Bmatrix} 0 & if\ T_t < T_{base} \\ T - T_{base} & if\ T_{base} \leq\ T_t \leq T_{opt} \\ T_{opt} - T_{base} & if\ T_t > T_{opt} \end{Bmatrix},$$

where t is an hour within the growing season; T_t is the average temperature during the hour and is determined by interpolating a sine curve between the minimum and maximum temperatures in a day; and N is the number of hours between planting and harvesting. Therefore, the $GDD_{8,30}$ corresponds to T_{base} = 8°C and T_{opt} = 30°C, and GDD_{30+} corresponds to T_{base} = 30°C and T_{opt} = infinity.

Precipitation is controlled for by summing the total precipitation 10 days before and 10 days after silking, controlling for anthesis.

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