The Welfare Effects of an Input Subsidy Program, Crop Diversification, and the Farm Size-Productivity Relationship in Sub-Saharan Africa Agriculture

A DISSERTATION
SUBMITTED TO THE FACULTY OF THE
UNIVERSITY OF MINNESOTA

BY

Sinafikeh Gemessa

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Advisor: Marc Bellemare

August 2019

Acknowledgements

First and foremost, I would like to honor the Almighty God for giving me the opportunity to pursue the PhD including by helping me write this dissertation. I have constantly relied on him to give me the strength to carry out the demanding responsibilities of being a graduate student, husband, and parent.

My heart-felt appreciation goes to my principal advisor, Marc Bellemare. This dissertation would not have taken the shape it has now without his continued guidance, honest opinion, and encouragement. The thesis has also benefitted greatly from comments and suggestions from my committee members Paul Glewee, Metin Cakir, and Alan Benson. On top of their invaluable inputs, I would also like to thank them for their flexibility in arranging the oral examinations.

I am also grateful for comments and suggestions on various versions of the first chapter from Hanan Jacoby, Ibrahim Keita, Maxwell Mkondiwa, Jacob Ricker-Gilbert, Kibrom Tafere, Chalachew Temesgen, and seminar participants at the University of Minnesota and University of Wisconsin-Madison.

My co-authors on the last two chapters namely Habtamu Fuje (chapter 2), Klaus Deininger (chapter 3) and Daniel Ali (chapter 3) also deserve special appreciation. I have learned a lot from their approach to research. Thank you also for your unmatched patience working with me on these projects.

Above all, this research was supported by the men and women farmers who generously shared their life's work, knowledge, and perceptions in personal interviews. I would also like to thank the World Bank, national statistical agencies, and their donors for making the survey data freely available. These types of initiatives are especially useful to graduate students who often face limited means and time to collect detailed survey data.

I gratefully acknowledge the financial support from the University of Minnesota that has covered all the costs for the first four years of my PhD study. I am also grateful for the faculty of the Applied Economics department who have invested so much in me through both formal classes and informal discussions. Sometimes, such discussions lead to research ideas and co-authored papers. It is such a joy to collaborate with Jay Coggins, Ibrahim Keita, Ian Luby, and Maxwell Mkondiwa on a paper that estimates the economic ramifications of geoengineering our planet's stratosphere to climate change. I hope we get to send that paper to a journal very soon.

I am also grateful for the friendships that I formed in the past five years both in and outside of the university. They are too many to name here, but I feel so blessed to have known each and I hope our friendships will continue well beyond these years! Our pastors Abebayehu, Alene, and Alem and their lovely families deserve special mention. They have been incredibly supportive of me and my family. May God bless you!

I am also deeply indebted to my wife, Kidist (Kiddy) Desalegn. We started this journey shortly after getting married. She braved the Minnesota cold, frustratingly long work-authorization process, a totally new culture, and a husband who spends a lot of time on his studies. She has been incredibly patient with me and always supportive. I am so happy to have you in my life!

Kiddy and I have had our two kids while in graduate school. Our daughter Elise is almost four years of age and Barock turns two in November. I always say they are my second and third "PhD projects". While taking care of two little children is no small task, it has been an incredibly rewarding experience. I find that they are the perfect antidotes to the everyday stresses and frustrations of grad life. Elise and Barock, when you are old enough to read and understand this, know that you have helped daddy in more ways that you can ever imagine! I hope your own kids will be such a great therapy for you!

My parents Asrat Gemessa and Fantaye Ararso deserve special thanks. Despite their advancing ages, they have stepped up their support for my family when we needed it most. My two sisters, Abeba and Hiwot, and brother-in-law, Leulseged Aklilu, have been there for us in more ways than anyone can hope for. My four nephews and niece have made our family visits so delightful! My Aunt, Shibre Tabore, have always kept us in her thoughts and prayers. Thank you!

My mother-in-law, Genet Alemayehu, have spent months with us taking care of the kids while I was extremely busy with school and work. Words cannot express our gratefulness. My sisters-in-law Elsabeth and Rahel, their husbands Abiy and Andy, and their kids are among our biggest cheerleaders and supporters. Thank you!

Finally, we are grateful for our host Feleke and Aster, their kids, as well as Lakech and Tessemma for their hospitality ever since we arrived in Minnesota.

Dedication

To my wife, Kidist, and my two kids Elise and Barock.

You have made this journey not only bearable but enjoyable.

Abstract

This dissertation is composed of three essays all dealing with sub-Saharan African Agriculture. In the first essay, I apply a relatively novel approach to the evaluation of input subsidy programs (ISPs) by estimating the consumer surplus accrued by direct beneficiaries of ISPs. I use this method to evaluate the welfare impact of subsidizing fertilizer for smallholder farmers in Malawi—a country that has the largest ISP in sub-Saharan Africa. In the second essay, we investigate the linkages between crop diversification, poverty, and experience with crop shocks in the context of Malawi. These relationships are less known in the literature that mostly shed light on the relationship between crop diversification and welfare outcomes such as dietary diversity, agricultural productivity, and education. In the last essay, we revisit the oft-observed inverse relationship (IR) between farm size and productivity in the development literature. Almost all the empirical investigations focus on smallholder agriculture. However, compared to small-scale farming, large commercial farms are considered to have the upper-hand in agricultural technological innovation, access to better inputs and mechanized farming, and economies of scale. It is, however, an open question whether they can reverse the IR between farm size and productivity. This paper investigates this relationship over large variations of farm sizes and different measures of productivity.

Table of Contents

List of Tables

List of Figures

1. Introduction

This dissertation focuses on three issues of concern in sub-Saharan African agriculture. In the first essay, we estimate the welfare impact of a large input subsidy program (ISP) in Malawi. After falling out of fashion in the 1990s, ISPs are getting renewed attention by different stakeholders in Africa. This essay seeks to expand the methodological arsenal in evaluating such programs. In the second essay, we investigate the linkages between crop diversification, poverty, and experience with crop shocks in the context of Malawi. These relationships are less known in the literature. In the last essay, we revisit the inverse farm size-productivity relationship that has been well documented for smallholder agriculture. This essay examines this inverse relationship over large variations of farm sizes and for different major grain crops grown in Ethiopia. The following paragraphs summarize the essays in more detail.

Essay 1: Most studies that have evaluated the welfare impacts of agricultural input subsidy programs (ISPs) in developing countries have focused on measuring their effects on various outcomes of interest such as agricultural productivity. I apply a novel approach to the evaluation of ISPs by estimating the consumer surplus accrued by direct beneficiaries of ISPs. I use this method to evaluate the welfare impact of subsidizing fertilizer for smallholder farmers in Malawi. Malawi's Farm Input Subsidy Program (FISP), introduced in 2005, is the largest such scheme in sub-Saharan Africa. I find that the program provides low direct benefits compared to the public costs of the program. At the national level, the benefit-cost ratio (BCR) is 0.43 for FISP households with no option to resell the fertilizer accessed through the program. When reselling of the fertilizer is allowed for, the BCR increases to about 0.67. The program is also regressive given that more than 60 percent of all fertilizer vouchers and benefits accrued to farm households with above the median wealth level. I find that many farmers demand 20 kg of fertilizer or less at the subsidized price. Thus, when these farmers have the option to buy 20 kg bags of fertilizer in addition to the 50 kg bags currently being offered under FISP, their benefits increase by about 18.6% compared to the status quo. Overall, my results suggest that a more flexible redemption of the fertilizer vouchers as well as complementary investments such as improved access to credit would substantially increase the program's contribution to farmers' welfare.

Essay 2: Many studies that have examined the association between on-farm crop diversity and welfare outcomes have looked at measures such as dietary diversity, agricultural productivity, and education. However, the linkages between crop diversification, poverty, and experience with crop shocks are less understood. In this paper, we provide evidence for the unmediated association between crop diversity and the commonly used welfare measures in the context of Malawi.

Malawi's agriculture is highly dependent on a few commodities with maize as the staple crop and tobacco for export. We find that crop diversification appears to have further declined during 2004–2016, with little variation across regions and socioeconomic characteristics. We also find that diversified households have higher consumption per capita and are more likely to be non-poor after controlling for potentially confounding observable characteristics. The positive relationship between diversification and consumption (and hence higher chance of escaping poverty) is stronger for households in the bottom four consumption quintiles. Previous exposure to crop shocks such as disease, pest, drought, and flooding is also associated with higher crop diversifications. Evidence from this study suggests that poverty reduction policies and programs in rural areas could benefit farmers by supporting better crop diversification**.**

Essay 3: Almost all the empirical investigations into the oft-observed inverse relationship (IR) between farm size and productivity use data from smallholder agriculture. However, compared to small-scale farming, large commercial farms are considered to have the upper-hand in agricultural technological innovation, access to better inputs and mechanized farming, and economies of scale. As a result, investments in large-scale farming have been rising rapidly in land abundant developing and transitioning countries. It is, however, an open question whether they can reverse the inverse relationship between farm size and productivity that has been well documented for small-scale farming. This paper aims to answer this question by investigating the IR over large variations of farm sizes and for different major grain crops grown in Ethiopia. Our findings confirm the empirical regularity of the IR between farm-size and productivity for small-scale agriculture. This is true for each of the five major crops considered in this study. The results for medium- and large-scale farms are mixed. For medium-scale farms, we found no relationship between crop area and productivity for all the crops except Teff, in which case the IR is observed. For large-scale farms, the IR is maintained for all the crops except maize. These results are largely robust to the inclusion or exclusion of other inputs as controls and whether we use village or district level fixed effects.

2. An Alternative Approach to Measuring the Welfare Impacts of Input Subsidies: Evidence from Malawi

Sinafikeh Gemessa

2.1. Introduction

Are input market failures to blame for low agricultural productivity in sub-Sahara Africa? Many seem to think so, which explains the popularity of agricultural input subsidy programs (ISPs) in Africa. After falling out of fashion in the 1990s, ISPs are getting renewed attention by policymakers, donors, researchers, and other stakeholders. They are proposed as a way of addressing the widespread failure of agricultural input markets that constrain poor smallholder farmers from accessing adequate inputs. Recent ISPs often employ vouchers to target poor farmers and are so-called "smart" subsidies (Morris et al. 2007).[1]

By resolving an important market failure through access to cheap agricultural inputs, policymakers are hoping to improve agricultural productivity, thereby improving food security. This is especially true for net buyers of agricultural products as the increased production puts downward pressure on retail prices.[2]

Agricultural subsidies may have undesirable consequences, however. They could introduce deadweight losses that grow in magnitude with the inefficiency of the programs when the total cost of subsidies outweighs the sum of increased consumer and producer welfare that they generate. Leakages and diversion of subsidized inputs away from their intended beneficiaries is also a major concern (Chirwa and Dorward 2013). Furthermore, given the high administrative and fiscal burdens of agricultural subsidies in developing countries, it is often difficult to sustain such programs and the opportunity cost could be high.

What is the direct welfare impact of fertilizer subsidies to beneficiary farmers? Understanding the benefits and costs of agricultural subsidies is critical to public policy in many developing economies. To answer this question, I follow the welfare economics tradition of estimating

---

[1] The explicit targeting of vouchers to poor farmers by "smart" subsidy schemes is designed to reduce the share of benefits going to larger, wealthier, farmers for whom the subsidy is likely to be inframarginal. For these farmers, the subsidy acts just like a cash transfer.

[2] Increased agricultural supply in markets have ambiguous long-term impact on net-sellers' welfare. The decreased profit per unit of sold output as a result of lower market prices will adversely impact their welfare while expanding their marketable agricultural output does the opposite.

consumer surplus accrued to beneficiary farmers—a method rarely applied in the context of ISPs—to the case of Malawi's Farm Input Subsidy Program (FISP). Malawi presents an important case study for input subsidies. The FISP, introduced in 2005, is the largest such scheme relative to GDP in sub-Saharan Africa (Jacoby 2016). The main objective of the program is to achieve food self-sufficiency and increased income for poor households through better access to farm inputs and adoption of improved technologies in maize and legume production systems.

The government runs FISP by distributing vouchers to pre-selected farmers every year. This way, up to 50% of Malawian farm households have been targeted to receive vouchers. Targeted farmers can then redeem the vouchers in exchange for fertilizer and improved crop seeds. The inputs are highly subsidized. In 2016/15, for example, farmers paid only 3,500 Malawian Kwacha (or 5.5 current US dollars) per 50 kg bag of fertilizer—or about 20% of the average commercial value of the bag—to redeem the fertilizer vouchers. The government has consistently been allocating 7% to 9% of its total budget on agricultural input subsidies since 2005-06 (Chirwa et al. 2016).

The program has garnered widespread attention after its deployment. Sachs, for example, declared that the program has resulted in doubling of production in just one harvest season after its introduction (Sachs, 2012). It has also influenced other African governments including in Tanzania, Zambia, Kenya, and Rwanda to follow the example of Malawi by implementing some form of input subsidy programs (Messina et al. 2017). By 2010, at least nine African countries had introduced agricultural input subsidies (Jayne and Rashid, 2013).

Despite the resurgence of ISPs, there have been only a few studies that have rigorously estimated their welfare impact across different sub-Saharan African countries (Kelly et al., 2011 and Morris et al., 2009). Lack of good quality data and the use of agricultural subsidies as mainly political tools by African policymakers to garner support with little or no research input have contributed to the paucity of studies.

This study is closest in spirit to Jacoby (2016). He uses a consumer surplus estimation approach to estimate the welfare impact of FISP. As discussed below, this study makes significant methodological improvements to Jacoby's study. Other studies have focused on measuring the effects of ISPs on various outcomes of interest such as agricultural productivity and prices. Mason et al. (2013), for example, estimate Zambia's input subsidy program on maize intensification, extensification, and output. On Malawi, studies on the impact of FISP have focused on its impact on commercial fertilizer markets (Jayne et al. 2013 and Ricker-Gilbert et al. 2011), maize yield, output, and prices (Messina et al. 2017; Ricker-Gilbert et al. 2013, and Jayne et al., 2013), self-assessment of wellbeing and schooling outcomes (Chirwa et al. 2011), reported incomes and value of assets (Ricker-Gilbert 2011 and Holden and Lunduka 2010), and economy-wide impacts of the program using general equilibrium analysis (Arndt et al., 2016 and Chirwa and Dorward 2013).

The main results of some of these papers have been contradictory. For example, Ricker-Gilbert (2011) finds no impact of the subsidy on non-farm income or on total household income while Chirwa et al. (2011) find generally positive impacts on self-assessed well-being. In a notable exchange between Dorward and Chirwa (2015) and Jayne et al. (2015), the authors of the two papers disagree on the methodology for estimating the economic benefit cost ratio (BCR) and the fiscal efficiency of FISP. [3] More recently, Messina et al. (2017) present new evidence and report on a data error that led to the 'Malawi miracle' narrative in relation to FISP. The authors then surmise that the "Malawian production miracle appears, in part, to be a myth". The question of the welfare implications of FISP is, therefore, far from being settled.

This paper makes three main contributions. First, it contributes to the debate on the impact of FISP from the perspective of a novel methodology that is rarely applied to evaluate ISPs. More specifically, I apply the welfare economics tradition of estimating consumer surplus associated with FISP by treating beneficiary farmers as "consumers" of fertilizer. To do this, I first estimate the demand for fertilizer as a function of fertilizer and output prices, overall wealth levels, size of land under cultivation and many other controls. This allows me to estimate the willingness-to-pay (WTP) for fertilizer, which can be used to measure the benefits (and costs) of policy interventions. The consumer surplus implied by FISP is thus the mathematical area under the fertilizer demand curve and bounded from above and below by the commercial and subsidized price of fertilizer respectively (see section 3 for a detailed discussion of this methodology). This represents the welfare impact of the program as it is equivalent to farmers' valuation of current and future benefits of subsidized fertilizers net of costs. Thus, it is also more comprehensive than looking at the impact

[3] One point of disagreement, for example, is that Dorward and Chirwa (2015) argue that the low economic BCR of the program that Jayne et al. (2013) found is partly due to exclusion from the benefits of fertilizer those that have been diverted (or stolen) from the program. Jayne et al., (2015) re-estimated their BCR by including diverted fertilizer as benefits and found that the BCRs are higher than when diversion is not allowed.

of the program on contemporaneous farm output and income, which has been the focus of most studies mentioned above.

To the best of my knowledge, the only other paper that implemented this methodology is Jacoby (2016). Like this paper, he also focuses on Malawi's FISP. He first estimates a fertilizer demand equation by restricting his sample to non-beneficiaries in order to take advantage of the variation in fertilizer purchase. He then estimates a consumer surplus for beneficiary farmers using the fertilizer demand parameter estimates obtained for non-beneficiary farmers. To do this, he assumed that the fertilizer demand behavior of non-beneficiaries is, on average, similar to the behavior of the beneficiaries. He also does not consider reselling of the subsidized fertilizer by beneficiary farmers.

The current paper improves upon Jacoby (2016) in three major ways. First, while I also estimate the fertilizer demand equation using only non-beneficiaries (see section 5 for more on the justification), I control for unobserved heterogeneity in farmer characteristics that are fixed over time using farmer fixed effects. In contrast, Jacoby (2016) relies on cross-sectional analysis to estimate his fertilizer demand equation. These unobserved characteristics such as the negotiation ability of the farmer, which could marginally affect the selling price of fertilizer for the farmer in the commercial input market, could contaminate the estimates from the cross-sectional analysis. Second, unlike Jacoby (2016), I match non-beneficiaries with beneficiaries based on their propensity to be targeted by the program. This helps reduce the bias due to observable differences between the two groups. Third, in my estimation, I explicitly account for the possibility of redistribution and resell of subsidized fertilizer by beneficiary farmers. Indeed, this is reported to be a common feature of the program (see, for example, Chirwa and Doward 2013 and Holden and Lunduka 2010).

The second contribution of the paper is that I evaluate FISP after it has undergone significant reform in the 2015/16 planting season. The main change was that the price that farmers were required to pay to get the subsidized fertilizer was raised from just 500 Malawian Kwachas (MK) per 50 kg bag in prior years to 3,500 MK per 50 kg bag (Chirwa et al. 2016). This represents a 7-fold increase in subsidized prices and farmers' contribution increased from just 5% to about 20% of the total value of the fertilizer vouchers. This will surely reduce their consumer surplus. Almost all previous studies of FISP were done when farmers were receiving close to a full subsidy. Policymakers care more about the impact of FISP after these major changes were put into effect, as more recent iterations of FISP are similar in design with the program I evaluated with data from 2016/17.

The third contribution is that I also estimate the potential impact of the FISP under flexible redemption of the fertilizer vouchers. Currently, beneficiary farmers can redeem the fertilizer vouchers for only 50 kg bags. However, this may not be the amount that many farmers demand at the subsidized price. Results from my fertilizer demand analysis show that many farmers demand 20 kg of fertilizer or less, on average, at the subsidized price. Thus, I calculate the welfare implications of the FISP also for the case when farmers have the additional option to redeem their vouchers for 20 kg bags on top of the 50 kg bags currently on offer. Such flexibility of voucher redemptions has not been explored before.

Overall, I find low direct benefits compared to the costs of the program. At the national level, each Malawian Kwacha spent for subsidizing fertilizer yielded a benefit of only about 0.43 Kwacha. This is for the scenario where beneficiary households have no option to engage in the secondary market for FISP fertilizer (i.e., without the option to resell or buy the program fertilizer from this market). With the option to participate in the secondary market, the benefit—cost ratio (BCR) increases to as much as 0.67. Moreover, when farmers have the additional option to buy 20 kg bags of the fertilizer as opposed to only the 50 kg bags currently being offered under FISP, their average benefits increase by about 18.6% compared to the status quo for those famers that demand 20 kg of fertilizer or less at the subsidized price.

The remainder of this paper is organized as follows. Section 2 discusses FISP in more detail. Sections 3 and 4 present the conceptual framework and empirical model, respectively. Section 5 describes the data, while estimation strategies are articulated in Section 6. Section 7 presents the empirical results. The last section concludes the paper.

2.2 Overview of Malawi's Farm Input Subsidy Program (FISP)

Poor harvests in Malawi in the early 2000s led to high food prices and food shortages. The situation was particularly bad in 2005, when uncertainty about a proposed subsidy program coupled with drought left about 4.91 million Malawians vulnerable to hunger and food insecurity (Malawi Vulnerability Assessment Committee 2005; Sahley et al., 2005).

Starting in 2005/06, the Government of Malawi has implemented the national Farm Input Subsidy Program (FISP) to target resource-poor farmers. The main objective of the FISP has consistently been to make improved agricultural inputs accessible to vulnerable and resource-poor smallholder famers. The stated purpose of the program is to achieve individual and national food self-sufficiency and to raise beneficiary famers' incomes through increased maize and legume production (Chirwa and Dorward 2013).

The FISP is the largest agricultural subsidy relative to GDP in sub-Saharan Africa. The government has been allocating between 7% and 10% of the national budget annually to the FISP (Chirwa et al., 2016). The program targets up to 50% of farmers in the country to receive vouchers that can be redeemed for fertilizer and improved maize and legume seeds. In 2015/16, the planting season covered by the data used in this study, targeted farmers were expected to make payments of 3,500 Malawi Kwachas (MK) per 50 kg bag, or about 20% of the total value of the vouchers, upon redemption. The fertilizer subsidy component of the FISP, which is the focus of this paper, typically constitutes over 80% of public expenditure on the program. Fertilizer vouchers have been distributed in a package of two vouchers, one for a 50 kg bag of 23:21:0 +4S basal fertilizer (NPK) and one for a 50 kg bag of urea for top dressing.

In the 2015/16 planting season, the government instituted significant changes to FISP. These include: 1) increasing farmers' contribution to the FISP fertilizer from MK500 per 50 kg bag to MK3500 per 50 kg bag upon voucher redemption; 2) re-introduction of the private sector in the distribution and retail of subsidized fertilizer in select districts; and 3) central selection of beneficiaries using random methods to address bias at the village level (Chirwa et al., 2016). Despite the claim of random targeting, I found systematic differences between voucher recipients and non-recipients during the 2015/16 planting season (see Table 4). This suggests that village heads continued to influence targeting outcomes.

Prior to 2015/16, the targeting criteria under the FISP were lax and community leaders often exercised discretion in identifying program beneficiaries (Houssou and Droppelmann 2013). This lack of clarity on the criteria also led local leaders and government staff to frequently engage in redistribution of fertilizer coupons. Consequently, the proportion of households who received just one fertilizer voucher has increased since the program's introduction (Dorward and Chirwa 2013).

Many studies have provided evidence of poor targeting of the program in relation to its objectives (Chirwa et al., 2016; Chirwa and Dorward, 2013; Jayne et al., 2013). These studies report that leakages and diversions of the vouchers or program fertilizers to richer farmers have been the enduring features of the program. This paper confirms the trend. In 2015/16, about 60% of total fertilizer vouchers and benefits, as measured by net consumer surplus, went to farm households with higher than median wealth level.

2.3. Conceptual Framework

Household farm production and consumption decisions are unlikely to be separable in developing countries. This is because of imperfect input and output markets such as limited access to rural credit and to consumer goods that constrain farmers from accessing the desired type and level of inputs and outputs. Thus, a household's socio-demographic characteristics will intervene its input use decisions (de Janvry and Sadoulet 2006).

Following Ricker-Gilbert et al. (2011), fertilizer demand is assumed to take the form

$$F = f\left(P_f, P_a, T, Z, A\right) \qquad [1]$$

where F is the quantity of fertilizer purchased; P_f is the price of commercial fertilizer; P_a is the output price of the agricultural good such as maize; T represents the fixed cost of using fertilizer, such as transport costs; Z includes household sociodemographic characteristics; and A captures the quantity and quality of land.

2.4. Empirical Strategy

Economic theory states that demand as a function of prices reflects marginal valuation or willingness-to-pay (WTP) for the good demanded. It can thus be used to measure the benefits (and costs) of policy interventions.

In this paper, I assume that farmers choose agricultural input combinations that maximize their utility given their access to liquidity, land, and other complementary inputs. Furthermore, the fertilizer demand equation that I estimate includes both agricultural supply side variables such as cultivated land area and labor and demand side variables such as level of wealth. This allows me to test whether farmers make joint or separable production and consumption decisions. If there is no market failure in the input credit market, for example, wealth should not be a significant determinant of the demand for fertilizer as farmers can access adequate credit to cover the cost of the amount of fertilizer that maximizes their expected utility regardless of their wealth level.

The empirical application will, therefore, involve first estimating a demand curve for fertilizer using micro-data and then estimating "consumer surplus" changes implied by the FISP. All along, I treat beneficiary farmers as "consumers" of fertilizer. That is, like any ordinary consumer good, farmers' demand for fertilizer is a function of attributes of the fertilizer (such as its price and nutrient content) and other conditioning factors.

Following Ricker-Gilbert et al (2011), the amount of fertilizer type j demanded by household i at year t, f_{ijt}, is assumed to take the form

$$\text{arcsinh}\,(f_{ijt}) = \alpha_j X_{ijt} + \gamma_j W_{ijt} + \beta_j \,\text{arcsinh}(p_{ijt}) + \delta_t + \varepsilon_{ijt}, \qquad [2]$$

Where arcsinh refers to the inverse hyperbolic sine transformation. It is similar to the log transformation but allows for zero and even negative values.[4] The key variable is p_{ijt}, the farm-gate price of fertilizer type j faced by farm household i at year t while $\alpha_j X_{ijt}$ represents the linear combination of plot and socio-economic characteristics (such as household size, size of cultivated land, and soil quality measures) for a farm household i that demands fertilizer type j at year t. The variable W_{ijt} is the wealth index for farm household i that demands fertilizer type j at year t. In section 5, I discuss how this index is constructed. The coefficient δ_t is for the year dummy. In the following analysis, I include W_{ijt} and δ_t into the vector X_{ijt} for ease of presentation. The error term is represented by ε_{ijt} and it includes unobservable characteristics such as measurement error in the dependent variable. The key coefficient β_j represents the price elasticity of demand for fertilizer type j to changes in farm-gate price p_{ijt}.

Following Jacoby (2016), five different fertilizer demand scenarios are considered based on the shape of the demand curve and where it crosses the vertical price axis (also known as choke price). See Figure 2-1 for an illustration.

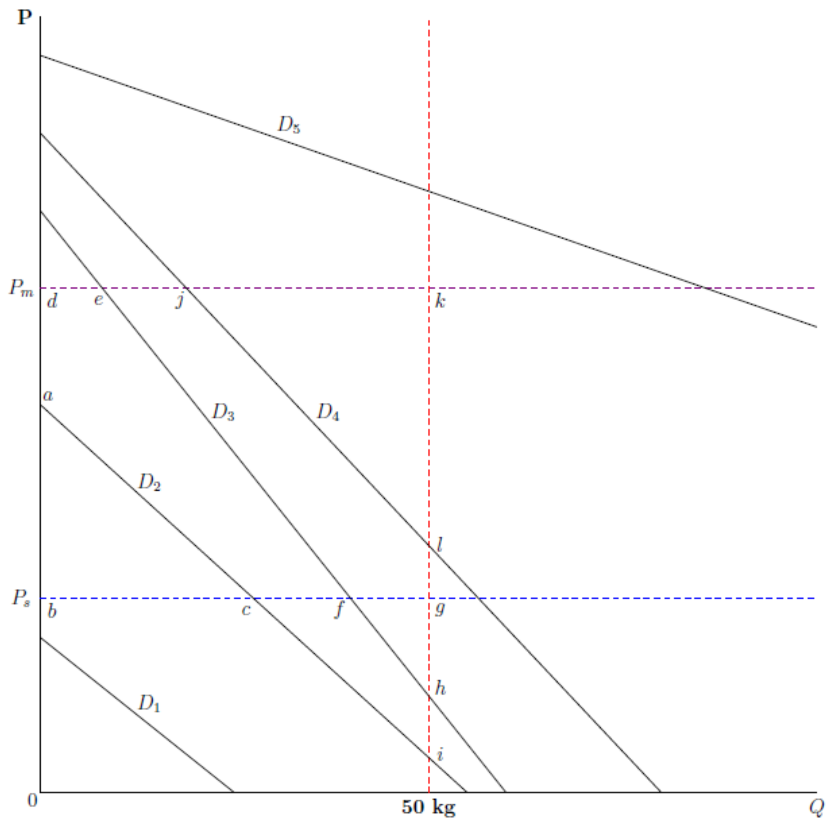
The first demand scenario represented by the demand curve D1 in Figure 2-1 shows a demand for fertilizer that is so low that none would be purchased at the subsidized price (P_s). In scenarios 2 and 3, farmers would have liked to buy less than 50 kg (but not 0 kg) of subsidized fertilizer at P_s. Thus, beneficiary farmers described by scenarios 2 and 3 redeem the voucher only if the net benefit exceeds zero. That is, for demand scenario 2, for example, area of the triangle 'abc' in Figure 2-1 must exceed area 'cgi'. Here note that redemption forces the farmer to purchase a whole 50 kg bag at the subsidized price of 70 MK/kg (P_s) even though in this case the farmer's willingness to pay at P_s is less than 50 kg. Unlike the first two scenarios, the beneficiary farmers represented by the

[4] More precisely, $\text{arcsinh}(f_{ijt}) = ln\left(f_{ijt} + \sqrt{{f_{ijt}}^2 + 1}\right)$. It approximates the log transformation over positive values.

scenarios 3 and 4 (or D3 and D4 in Figure 2-1) would buy some fertilizer at the market price in the absence of FISP. In scenario 4, the farmer is willing to buy more than 50 kg at P_s but less than this amount at the market price P_m.

Lastly there is the purely inframarginal subsidy represented by scenario 5. Here, the subsidy acts like a cash transfer and the total fertilizer purchased will not change because of the subsidy. As a result, the welfare gain, $(P_m - P_s) * 50$, or the area 'bdkg' in Figure 2-1, is equal to the cost of the subsidy to the government. Note also that scenario 5 is the only situation where the subsidy benefits the farmer and does not result in a deadweight loss other than the deadweight loss of taxes to pay for the subsidy. The consumer surplus implied by FISP is thus the mathematical area under the fertilizer demand curve and bounded from above by the commercial price of fertilizer (P_m) and from below by the subsidized price of fertilizer (P_s). Table 2-1 shows the region of net welfare gain for each scenario represented by the demand curves in Figure 2-1. As will be discussed in the empirical results section, each beneficiary farmer in the dataset falls into one of the five demand scenarios.

Figure 2-1: Illustration of Fertilizer Demand Scenarios



Note: P_m = market or farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer). Points 'i', 'h', and 'l' represent WTP for one 50 kg bag of fertilizer for demand scenarios 2 to 4 respectively.

Table 2-1: Consumer Surplus Regions for Each Demand Scenario Presented in Figure 2-1

Fertilizer demand scenarios	**Region of net consumer surplus based on Figure 2-1**
1: no demand at P_s (i.e. P_s > choke price)	0
2: WTP for one bag < P_s < choke price <P_m	Area (abc) – Area (cgi)
3: WTP for one bag < P_s <P_m < choke price	Area (bdef) – Area (fgh)
4: P_s < WTP for one bag <P_m < choke price	Area (bdjlg)
5: P_m < WTP for one bag (inframarginal)	Area (bdkg)

Note: P_m = farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer); for the scenarios 2 and 3, the farmer redeems the voucher only if the first term exceeds the second.

Table 2-2 below shows the consumer surplus equations that correspond to the functional form used in equation (1) for a farmer who redeems a voucher for a single 50 kg bag of either NPK or urea.

These equations are derived by integrating the area to the left of the demand curve given in equation 1. Appendix A1 shows the mathematical derivation of the integral. As expected, the net welfare gain equations differ for different demand scenarios.

Table 2-2: Major Demand Scenarios and Net Consumer Surplus Estimation Equations from Redeeming a Fertilizer Voucher

Fertilizer demand scenarios	Net consumer surplus estimation equations
D1: no demand at P_s (i.e. P_s > choke price)	0
D2: WTP for one bag < P_s < choke price <P_m	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j + 1}\left(P_{cijt}{}^{\beta_j+1} - P_{bagijt}{}^{\beta_j+1}\right) - \left(P_s - P_{bagijt}\right) * 50$
D3: WTP for one bag < P_s <P_m < choke price	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j + 1}\left(P_{mijt}{}^{\beta_j+1} - P_{bagijt}{}^{\beta_j+1}\right) - \left(P_s - P_{bagijt}\right) * 50$
D4: P_s < WTP for one bag <P_m < choke price	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j + 1}\left(P_{mijt}{}^{\beta_j+1} - P_{bagijt}{}^{\beta_j+1}\right) + \left(P_{bagijt} - P_s\right) * 50$
D5: P_m < WTP for one bag (inframarginal)	$\left(P_{mijt} - P_s\right) * 50$

Note: p_{mijt} = the market or farm-gate price of fertilizer type j faced by farmer i at year t; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer); P_{bagijt}= WTP per kg for one bag (50 kg) of fertilizer type j by farmer i at year t; P_{cijt}= is the choke price or the price at which farmer i demands zero amount of fertilizer type j (or the price at which the demand curve crosses the vertical axis in Figure 2-1) at year t. All prices are in MK/kg. The vector $\alpha_j X_{ijt}$ represents the linear addition of controls multiplied by their coefficients for farmer i at year t. For the scenarios 2 and 3, the farmer redeems the voucher only if the first term exceeds the second.

So far, I have assumed that beneficiary farmers do not engage in side-selling and buying of the program fertilizer that they received. Indeed, the extent of side-selling of subsidized fertilizer is difficult to capture using a survey setting as it is illegal in Malawi for beneficiary farmers to resell the fertilizer they received through the FISP. However, in practice, due to weak enforcement, many studies report that substantial percentage of beneficiary farmers resell some or the entire fertilizer received through the FISP (e.g. see Chirwa and Doward (2013) and Holden and Lunduka (2010)).

In this paper, I account for potential resell of subsidized fertilizer by beneficiary farmers that belong in the first three demand scenarios. As discussed earlier, these farmers prefer to buy less than 50 kg of subsidized fertilizer of either type. Thus, they are more likely to engage in side-selling of the program fertilizer. By contrast, FISP households represented by demand scenarios 4 and 5 are assumed to buy from the resellers. This is because they demand more than 50 kg of the fertilizer at the subsidized price (see Figure 2-1).

To estimate the resell price, I use the data reported by Chirwa et al (2016) and Holden and Lunduka (2010). Holden and Lunduka (2010) found the median price for the secondary market of fertilizers accessed through the FISP to be 90 MK per kg in 2008/09, when the commercial price of fertilizers was at about 200 MK/kg. This is 45% of the market price. Chirwa et al (2016) use data from the national Logistics Unit and estimate that about 62% of the total fertilizer under FISP was distributed through contract arrangements (i.e. government) at the cost of MK 413.66 per kg while the remaining 38% of the fertilizer was delivered through the private sector for MK 360 per kg in the 2015/16 planting season. The weighted national average value of the voucher is thus 393.5 MK per kg or MK 19,675 per 50 kg bag. Following Holden and Lunduka (2010), the median resell price of program fertilizer would, therefore, be around 45% of the commercial value of the vouchers or about 177.1 MK/kg in 2015/16.

I thus recalculate beneficiaries' consumer surplus by allowing them to engage in the secondary market for program fertilizer at the estimated median resell price of 177.1 MK/kg (denoted by P'_m). I also estimate the consumer surplus derived if they sell at the break-even or subsidized price (70 MK/kg or P_s). This is similar to redistribution of the subsidized fertilizer accessed through the FISP. Additionally, I assume that farmers who belong in the first demand scenario resell the entire redeemed fertilizer whereas farmers in demand scenarios 2 and 3 resell only the portion of subsidized fertilizer that exceeds their demand at P_s . That is, if, for example, they were to resell the fertilizer they do not need at subsidized price), farmers represented by demand scenarios 2 and 3 will fully recoup the loss they incurred as represented by areas 'cgi' and 'fgh' in Figure 2- 1 respectively. In practice, this is likely to be an upper bound on the impact of reselling since not all farmers will have the opportunity to resell due to the illegality of the practice in Malawi (albeit with weak enforcement), the risk of losing eligibility in the future, and transaction costs such as transportation expenses.

Table 2-3 shows the resulting net consumer surplus estimation equations that take these assumptions into account. Later in this paper, I report the average welfare gains or net consumer surplus amounts and subsequent analysis with and without the fertilizer resell option.

Table 2-3: Net Consumer Surplus Estimation Equations from Redeeming a Fertilizer Voucher with Resell

Fertilizer demand scenarios	Net consumer surplus with resell at P_s
D1: no demand at P_s (i.e. P_s > choke price)	0
D2: WTP for one bag < P_s < choke price <P_m	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}\left[P_{cijt}{}^{\beta_j+1} - P_s{}^{\beta_j+1}\right]$
D3: WTP for one bag < P_s <P_m < choke price	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}\left[P_{mijt}{}^{\beta_j+1} - P_s{}^{\beta_j+1}\right]$
D4: P_s < WTP for one bag <P_m < choke price	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}\left[P_{mijt}{}^{\beta_j+1} - P_s{}^{\beta_j+1}\right]$
D5: P_m < WTP for one bag (inframarginal)	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}\left[P_{mijt}{}^{\beta_j+1} - P_s{}^{\beta_j+1}\right]$
	Net consumer surplus with resell at P'_m
D1: no demand at P_s (i.e. P_s > choke price)	$(P'_m - P_s) * 50$
D2: WTP for one bag < P_s < choke price <P_m	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}\left[P_{cij}{}^{\beta_j+1} - P_s{}^{\beta_j+1}\right] + (P'_m - P_s) * (50 - F_{ij}(P_s))$
D3: WTP for one bag < P_s <P_m < choke price	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}\left[P_{mij}{}^{\beta_j+1} - P_s{}^{\beta_j+1}\right] + (P'_m - P_s) * (50 - F_{ij}(P_s))$
D4: P_s < WTP for one bag <P_m < choke price	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}[\left(P_{mij}{}^{\beta_j+1} - P_m{}^{\prime(\beta_j+1)}\right) + (P'_m - P_s) * 50$
D5: P_m < WTP for one bag (inframarginal)	$\frac{e^{\alpha_j X_{ijt}}}{\beta_j+1}\left[P_{mij}{}^{\beta_j+1} - P_m{}^{\prime(\beta_j+1)}\right] + (P'_m - P_s) * 50$

Note: p_{mijt} = the market or farm-gate price of fertilizer type j faced by farmer i at year t; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer); P_{bagijt}= WTP per kg for one bag (50 kg) of fertilizer type j by farmer i at year t; P_{cijt}= is the choke price or the price at which farmer i demands zero amount of fertilizer type j (or the price at which the demand curve crosses the vertical axis in Figure 2-1) at year t. All prices are in MK/kg $F_{ij}(P_S)$ = amount of fertilizer type j demanded at price P_s by farmer i of fertilizer type j. For D4 and D5, the net consumer formula applies only if the amount of fertilizer demanded at P'_m ($F_{ij}(P'm)$) is greater than 50 kg. If the demand is less than 50 kg at P'm, farmers do not buy the program fertilizer from the secondary market. The vector $\alpha_j X_{ij}$ represents the linear addition of controls multiplied by their coefficients for farmer i and fertilizer type j.

2.5. Data Description

The data used in this study come from the Integrated Household Panel Survey (henceforth IHPS) collected in Malawi in 2013 and 2016/17. In total, 1,908 households that were interviewed in 2013 were re-interviewed in 2016 with only 4% household-level attrition rate. The sample was selected to be representative at the national and urban/rural levels. The data include detailed information about households' socio-economic characteristics, agricultural and non-agricultural activities, consumption, and assets. Detailed plot level data are also collected.

Table 2-4 presents descriptive statistics on socio-economic and environmental characteristics of fertilizer voucher recipients and non-recipients for the second round survey (i.e. IHPS 2016/17). The descriptive statistics for IHPS 2013 is presented in Table A2-1 in the appendix. The variable "wealth index" is constructed by closely following the methodology adopted by the Demographic and Health Survey team for Malawi. Households are assigned a score based on how they rank on ownership of assets and other household characteristics. The assets include the number of rooms and the type of material of the floor, roof, and wall of the house, and whether the house is owned or rented. Ownership of radio, bicycle, bed, different types farm implements and livestock, among others are also included. Access to basic services such as toilet, clean drinking water, and cooking fuel are also accounted for. In addition to these, access to electricity, telephone, and a bank account are considered. These characteristics are then combined to create one summary measure of household wealth—called "wealth index" in this paper—using principal component analysis (PCA).

The descriptive statistics in Table 2-4 show that voucher recipients have acquired higher amounts of NPK and urea fertilizers, cultivate significantly larger amounts of land, and own more wealth. These indicate that the program is not pro-poor. Heads of voucher recipient households tend to be older and less educated than their counterparts among voucher non-recipients. They are also more likely to receive advice on fertilizer use. Beneficiaries of FISP also live on more elevated areas but are more likely to experience droughts. It is also important to highlight that significant proportions of both groups experienced droughts and irregular rains in the previous planting season. This is, indeed, in line with the 2015/16 El Nino-related widespread droughts and rain failures that led the Government of Malawi to declare a food emergency (Oxfam, 2016). The mean difference tests also show that beneficiaries are more likely to receive assistance through social safety net programs.

Strikingly, voucher recipients are more than 9 times more likely (28% Vs 3% for non-recipients) to list the village head or traditional authority among their close social networks.[5] This suggests that village heads still exert significant influence on the targeting outcome of the program. The mean soil quality index values are also significantly different between the two groups.[6] Note also

[5] Survey respondents were asked to name the 15 most important people in their social networks.

[6] In the IHPS data, each of the soil quality measures such as nutrient content and nutrient retention ability are ranked based on the level of constraints faced by the sampled household. The ranks range from "no or slight constraint" to "very severe constraint." These data are collected by the United Nation Food and Agriculture Organization (FAO's) Harmonized World Soil Database. The World Bank's data team has matched this external source with the IHPS data. The soil quality measures are then combined using PCA.

that only about 27% of sampled agricultural households in IHPS 2016/17 have received the fertilizer vouchers under FISP. A similar set of patterns can also be observed among voucher recipients and non-recipients in the 2013 round of IHPS (see Table A2-1 in the appendix).

Table 2-4: Descriptive Statistics for Fertilizer Voucher Recipients and Non-recipients in 2016/17

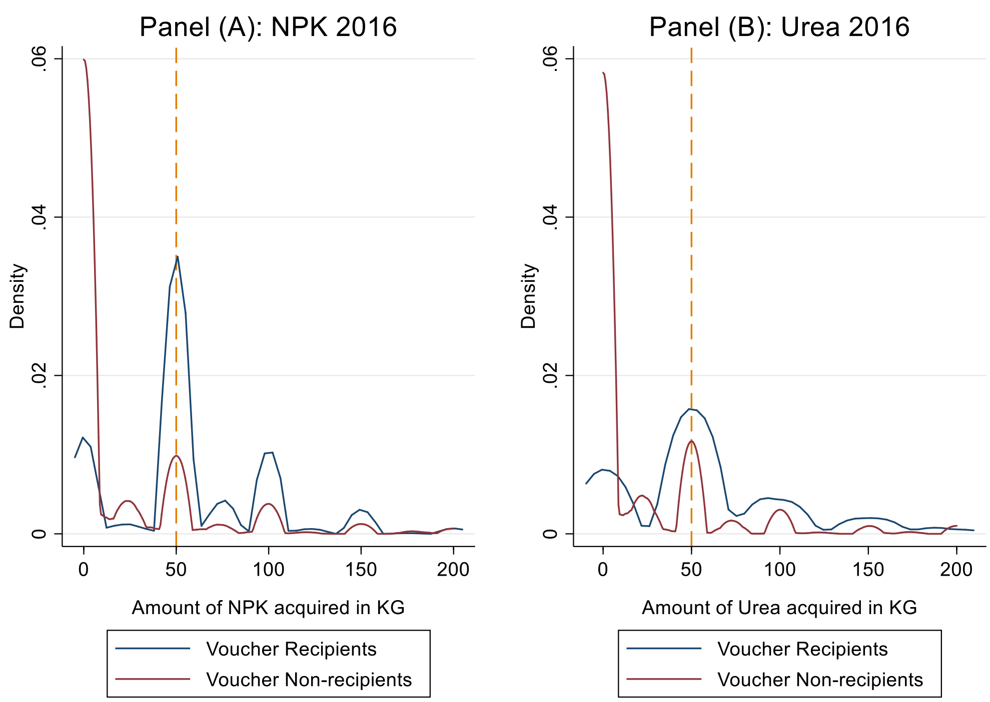
	Voucher non-recipients		Voucher recipients		|t test|
Variables	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**diff of means**
kg of NPK fertilizer acquired	23.12	56.29	68.74	178.29	45.62***
kg of urea fertilizer acquired	23.63	57.32	63.73	142.03	40.10***
Amount of land cultivated by HH (ha)	0.59	0.66	0.91	0.70	0.31***
Wealth Index	-0.24	2.57	0.82	2.31	1.06***
Farm credit org in village (=1 if yes)	0.39	0.49	0.37	0.48	-0.02
Household size	6.13	2.41	6.24	2.41	0.11
Female headed HH (=1 if yes)	0.24	0.43	0.24	0.43	-0.00
Age of HH head	44.21	13.32	46.98	14.45	2.77***
Years of education for HH head	6.04	4.05	5.37	3.59	-0.68***
Networked with village head or traditional authority (=1 if yes)	0.03	0.17	0.28	0.45	0.25***
Received advice on fertilizer use (=1)	0.29	0.45	0.33	0.47	0.04*
KM from HH to nearest agricultural market	21.73	15.43	26.69	15.24	4.96***
Log (elevation in meters)	6.66	0.60	6.78	0.36	0.12***
Log (annual precipitation in mm)	6.52	0.21	6.52	0.22	0.01
HH experienced drought (=1 if yes)	0.40	0.49	0.44	0.50	0.04*
HH experienced flooding (=1 if yes)	0.12	0.32	0.06	0.24	-0.05***
HH experienced irregular rain (=1 if yes)	0.68	0.47	0.70	0.46	0.02
HH received assistance through safety net (=1 if yes)	0.35	0.48	0.41	0.49	0.07***
Soil quality index	-0.05	1.37	0.12	1.50	0.17**
Number of households in sample	1,393		512		

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. The wealth and soil quality index values are calculated using principal component analysis method.

Source: Author's analysis from IHPS data for Malawi collected in 2016/17.

In addition to the average and standard deviation values, Figure 2 shows the nonparametric kernel distributions of the amount of NPK and urea acquired by voucher recipients and non-recipients in 2016/17. As expected, the vast majority of voucher recipients acquired a total of 50 kg of either type of fertilizer. On the other hand, only about 32% and 33% of voucher non-recipients bought commercial NPK and urea fertilizers, respectively. The distributions also show dissipating lumps in multiples of 50 kg for both beneficiaries and non-beneficiaries. This suggests that even voucher non-recipients may not have enough flexibility in terms of the amount of fertilizer they can buy from the market.

Figure 2-2: Kernel Distributions of the Amount of NPK and Urea Acquired in kg for Fertilizer Voucher Recipients and Non-recipients in 2016/17 Round



Source: Author's analysis from IHPS data for Malawi collected in 2016/17.

2.5.1. Commercial Price of Fertilizer Data

In the absence of historical data on the commercial price of fertilizer disaggregated by type at the community level, unit values of fertilizer are used to proxy commercial prices. Unit values are calculated by dividing expenditure on fertilizer by quantity of fertilizer purchased as reported by respondents.

Unit values present significant challenges to the analysis. Measurement error that are often associated with unit values could lead to attenuation bias. Unit values also represent equilibrium fertilizer prices as they indicate the prices at which the market exchange occurred.

To deal with some of these issues, I apply community median unit values to farmers who did not buy fertilizer commercially. This helps control for classical measurement error, and the median values are likely to reflect the actual commercial price of fertilizer as most farmers within the same community buy from one or very few commercial sources. As explained more below, I also estimate various fertilizer demand specifications with different control variables to make sure that the coefficients on the unit values are not spurious.

Unobservable quality differences are often the most important concern over the use of unit values in demand analysis of consumer goods (Deaton 1988). This is less relevant in this study as there are no documented quality differences between and within commercial and subsidized fertilizer.

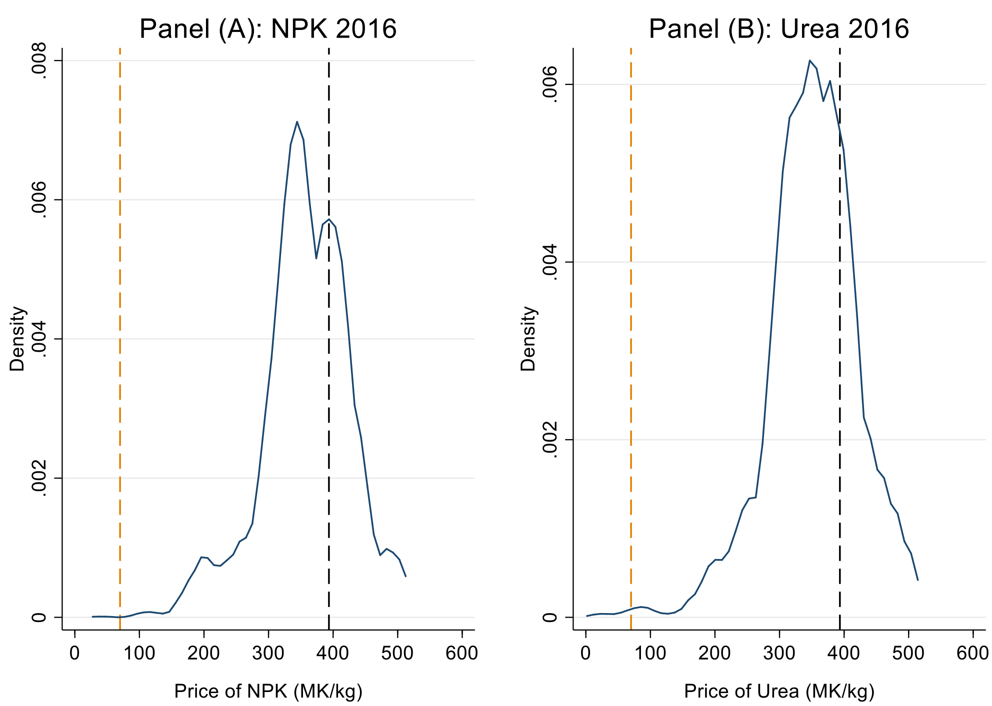
Note also that the counterfactual commercial price of fertilizer in the absence of the FISP is difficult to establish. This is not least because FISP has in the past resulted in some crowding out or displacement of the commercial fertilizer markets in Malawi (Ricker-Gilbert et al. 2011). This displacement occurred as FISP targets relatively non-poor farmers who would have bought fertilizer commercially. The impact of FISP on the commercial price of fertilizer is ambiguous, however. Compared to a non-FISP scenario, demand for commercial fertilizer will be lower due to the smaller number of commercial buyers resulting in downward pressure on equilibrium prices. At the same time, as retailers of commercial fertilizer pull out of the market in response to the reduction in demand, there would be an upward pressure on the equilibrium prices of commercial fertilizer. The equilibrium price will, therefore, depend on the relative strength of the two forces. Furthermore, the delivery record of fertilizers under FISP in 2015/16, the planting season considered in this study, is reported to be the worst compared to all the previous 11 years since its inception (Chirwa et al. 2016). Indeed, according to IHPS 2016/17 data, only about 27% of agricultural households received the fertilizer coupons in the 2015/16 season.[7] Thus, the displacement of commercial fertilizer market activity is likely to be relatively low in that year.

---

[7] FISP typically targeted 50% of farm households in Malawi in previous years (Chirwa and Dorward 2013).

In Figure 2-3, I present the distribution of the commercial price of fertilizer, disaggregated by type, using the IHSP data for the 2016/17 round. The figure shows largely similar distributions of commercial prices, with urea prices skewed slightly to the right of NPK prices. The first and second vertical dotted lines correspond to the subsidized price (70 MK/kg) and average public cost (393.5 MK/kg) of delivering the subsidized price, respectively. The public cost is calculated by closely following Chirwa et al (2016), which I will discuss in more detail in sub-section 7.4. As can be expected, the subsidized price of fertilizer belongs to the left tail of the distribution of commercial prices of fertilizer. The difference between the two vertical lines represents the net public cost of subsidizing the fertilizer. To make the commercial prices comparable between the two rounds, they are adjusted to national average general prices from October to December 2015. These months are the main planting season in Malawi.

Figure 2-3: Kernel Distributions of the Commercial Price of NPK and Urea in MK/kg



Note: The orange dotted line corresponds to the subsidized price of fertilizer (P_s) at 70 MK/kg. The blue-black dotted line corresponds to the average national public cost of delivering subsidized fertilizer under FISP at 393.5 MK/kg. The calculation of this figure is discussed in section 7.4.
Source: Author's analysis from IHPS data for Malawi collected in 2016/17.

.

2.6. Estimation Strategy

As discussed in section 3, the fertilizer demand equation to be econometrically estimated is shown in equation (2).

Estimation of equation (2) using data on only FISP beneficiaries is not appropriate. This is because beneficiaries, who are smallholder farmers, are less likely to participate in the commercial fertilizer market. Farmers targeted by the program pay a uniform price for subsidized fertilizer—3,500 Kwachas for 50 kg bag of NPK or urea since the 2015/16 planting season—making it difficult to estimate equation (2) directly using survey data for beneficiaries. There is, therefore, very small variation in the price and amount of fertilizer that beneficiaries acquire.

In addition to the small variation in fertilizer demand, beneficiaries of the FISP in Malawi are not selected randomly. Consequently, as shown in Table 2-4, non-beneficiaries are likely to be systematically different from voucher recipients. One, therefore, needs to be careful when using them as the control group. This further complicates the identification of the coefficients in equation (2). In this paper, I take the following measures to deal with these issues and to identify consumer surplus accrued to fertilizer voucher recipients.

To deal with the small variation of fertilizer demand for beneficiaries that face no variation in fertilizer prices under the FISP, I first estimate equation (1) by restricting my sample to voucher non-recipients in both rounds of the data. These non-beneficiaries buy fertilizer commercially, and farm-gate prices of fertilizer vary substantially for this sub-sample, as shown in Figure 2-3. Some 1,048 surveyed households in both rounds of the data (or about 55% of the sample) did not receive fertilizer vouchers in either round. The number of voucher recipients and non-recipients is presented in Table 2-5 below.

Table 2-5: Number of Voucher Recipients and Non-recipients in the Sample

	Voucher Recipients in a Single Round Only	Voucher Recipients in Both Rounds	Voucher Non-recipients in Both Rounds
Total	571*	289	1048

Note: * 348 and 223 households received vouchers only in 2013 and 2016/17 rounds, respectively.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

To deal with the non-random targeting of the program, I employ matching methods, as discussed below. Note also that each of the quartiles of the distribution of *a priori* important determinants of fertilizer, such as asset holdings and amount of land cultivated, are represented among both voucher recipients and non-recipients (Table 2-6). However, Table 2-6 also shows that more than half of voucher non-recipients belong to the bottom two quartiles of the wealth and land distributions. On the other hand, more than 60% of voucher recipients occupy the highest two quartiles of the wealth and land size distribution. The fact that the propensity score matching was done with replacement helps deal with the potential problem arising from the different distributions of the determinants of fertilizer demand.

Table 2-6: Distribution of Wealth and Amount of Land Cultivated for Fertilizer Voucher Recipients and Non-recipients (%) in 2016/17

	Wealth Index		**Amount of land cultivated**	
Quartile	**Voucher non-recipients**	**Voucher recipients**	**Voucher non-recipients**	**Voucher recipients**
1st	49.6	28.2	33.4	8.8
2nd	5.8	11.7	24.1	25.3
3rd	25.2	31.6	22.3	30.6
4th	19.4	28.4	20.2	35.3
Total	100	100	100	100

Note: The cut-off points on wealth and land size quartiles are calculated nationally after combining voucher recipients and non-recipients.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

In summary, my empirical estimation strategy consists of the following steps. I first estimate the fertilizer demand equation by restricting my sample to voucher non-recipients using a household and year fixed effects regression. This restriction achieves the necessary variation in fertilizer prices. Equation (1) is estimated separately for NPK and urea fertilizers, as they are complementary. I then estimate the welfare gain (in terms of consumer surplus) that would have accrued to non-recipients of fertilizer vouchers had they been targeted by the program (see Tables 2-2 and 2-3). This is similar to estimating the average treatment effect for the untreated—the treatment being the subsidy program. Practically, this amounts to estimating the net consumer surplus regions presented in Figure 2-1 for non-recipients. Voucher non-recipients were then matched with recipients using the nearest-neighbor propensity score matching method (Abadie and Imbens 2016). To implement this method, I make the standard assumption that farm households with very similar probabilities of being targeted by FISP also derive similar consumer surplus from the subsidy. Matching recipients with non-recipients on a wide-range of observable characteristics at the household and community level helps alleviate selection bias inherent in the nonrandom targeting of the program.

Note also that while the fertilizer demand equation is estimated using both rounds of the data—after adjusting for price differences between rounds—the welfare estimation associated with FISP was done using only the 2016/17 round. This is because the 2016/17 survey was conducted after FISP implemented significant changes in 2015, including increasing farmers' contributions from just 500 MK/bag to 3,500 MK/bag.

Other studies have used instrumental variable (IV) methods to control for potential endogeneity caused by nonrandom targeting of the FISP. Ricker-Gilbert et al. (2011), for example, estimate the demand for commercial fertilizer by using the number of years that the household head has lived in the village as an instrument for whether the household received the vouchers. By using matching methods in combination with consumer surplus estimation, this paper aims to contribute to the literature by applying a rarely applied method to study the welfare impacts of agricultural input subsidy programs.

2.7. Empirical Results

In this section, I present the fertilizer demand estimates in section 7.1. Matching fertilizer voucher non-recipients with recipients is done in section 7.2. Sections 7.3 and 7.4 present and discuss the results from the welfare estimations and benefit-cost analysis of the FISP program, respectively. The distribution of vouchers and benefits across different wealth quantiles are analyzed in section 7.5. The welfare implications under flexible redemption of fertilizer vouchers are discussed in section 7.6. Finally, section 7.7 summarizes the results of several robustness checks.

2.7.1. Fertilizer Demand Estimation

Demands for NPK and urea fertilizer were estimated using a household and year fixed effects regression. The results are presented in Tables 2-7 and 2-8. The full regression estimation results are reported in Tables A2-2 and A2-3. As discussed in the previous section, the demand regressions are restricted to non-recipients of the fertilizer vouchers, who face wide variation in market prices of fertilizer. I estimate the demand for each fertilizer type separately as they are complementary inputs. NPK fertilizer is used as a basal soil nutrient, while urea serves as top dressing to increase the nitrogen-based content of the soil. These fertilizer types are the only ones included in Malawi's fertilizer subsidy program.

Demand theory predicts that the price of fertilizer should negatively affect the quantity of fertilizer purchased, resulting in downward sloping demand curve. This is true for all the specifications considered in Tables 2-7 and 2-8, regardless of which control variables are used, including socio-economic characteristics, environmental factors such as elevation, rainfall, and experience with irregular rains, soil quality characteristics, and location and year dummies. The magnitudes of the own-price elasticities are also very similar across different specifications for each fertilizer type.

The results in Tables 2-7 and 2-8 also show that asset holdings and access to basic services, as measured by the wealth index variable, are positively associated with the demand for commercial NPK and urea fertilizer. As expected, the amount of land under cultivation is also positively associated with the demand for commercial fertilizer. The coefficient estimates on other variables are reported in Tables A2-2 and A2-3.

As a robustness check, I run the household and year fixed effects regression with the amount of cultivated land interacted with the soil quality index and with both linear and quadratic time-varying variables including the amount of rainfall in previous season, age of the household head, and the number of working age household members. The results are shown in Table A2-4 in the appendix. The coefficients on the covariates are very similar to the coefficients presented in Tables 2-7 and 2-8 and their expanded versions in the appendix. I estimate the welfare impact of the fertilizer subsidy using the last specification in Tables 2-7 and 2-8, as well as those presented in Table A2-4. The welfare implications using these estimates are similar to my main results. In section 7.7, I discuss the results from additional robustness checks.

The last columns of Tables 2-7 and 2-8 show that a one percent increase in the price of fertilizer is associated with reductions in demand for NPK and urea of about 0.80 and 0.84 percent, respectively. Furthermore, a one unit increase in wealth index is associated with about 0.5 and 3.4 percent increase in demand for commercial NPK and urea fertilizer respectively. This indicates that production and consumption decisions are not separable. In the presence of well-functioning credit markets, farmers should be able to obtain enough finance to buy the optimal amount of fertilizer. As a result, there should not be a significant relationship between asset holdings and amount of fertilizer purchased. It is, however, a common feature of agricultural markets in developing countries such as Malawi that credit markets are either not functioning properly—for example by requiring large collateral— or missing altogether. Consequently, farmers face liquidity constraints that preclude them from accessing adequate levels of fertilizer.

Table 2-7: Household Fixed Effects Estimates of Demand for Commercial NPK Fertilizer for Voucher Non- recipients

Variables	**Dependent Variable: Arcsinh (kg of commercial NPK fertilizer acquired per farm)**					
	1	2	3	4	5	6
Arcsinh (real price of fertilizer in MK/kg)	-0.791***	-0.851***	-0.763***	-0.783***	-0.784***	-0.794***
	(0.198)	(0.209)	(0.223)	(0.234)	(0.236)	(0.235)
Wealth Index			0.049***	0.052***	0.052***	0.051***
			(0.017)	(0.016)	(0.017)	(0.016)
Arcsinh (Amount of land cultivated by HH in ha)			1.556***	1.550***	1.553***	1.571***
			(0.268)	(0.264)	(0.265)	(0.265)
Constant	5.389***	5.003***	3.104*	8.907*	9.201*	8.308*
	(1.098)	(1.245)	(1.731)	(4.862)	(4.851)	(4.756)
Socio-econ variables	NO	YES	YES	YES	YES	YES
Fert Advise and distance to ag mkt	NO	NO	YES	YES	YES	YES
Environmental & soil quality variables	NO	NO	NO	YES	YES	YES
Agro-ecological dummies	NO	NO	NO	NO	NO	YES
Regional dummies	NO	NO	NO	NO	YES	NO
Number of unique observations	1,048	1,048	1,042	1,042	1,042	1,042
R-squared	0.026	0.034	0.116	0.132	0.133	0.136

Note: Robust standard errors clustered at Enumeration Area level in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; dependent variable, real price of fertilizer, and amount of land cultivated are transformed using inverse hyperbolic sine transformation. Fertilizer prices are adjusted to the average October to December 2015 national prices. The full regression results are presented in Table A2-2 in the Appendix.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table 2-8: Household Fixed Effects Estimates of Demand for Commercial Urea Fertilizer for Voucher Non- recipients

Variables	**Dependent Variable: Arcsinh (kg of commercial urea fertilizer acquired per farm)**					
	1	2	3	4	5	6
Arcsinh (real price of fertilizer in Kw/kg)	-0.755***	-0.833***	-0.846***	-0.832***	-0.832***	-0.835***
	(0.148)	(0.177)	(0.166)	(0.167)	(0.167)	(0.166)
Wealth Index			0.037**	0.035**	0.035**	0.036**
			(0.016)	(0.016)	(0.016)	(0.016)
Arcsinh (Amount of land cultivated by HH in ha)			1.525***	1.535***	1.536***	1.529***
			(0.292)	(0.293)	(0.295)	(0.293)
Constant	5.227***	5.176***	3.361**	5.283	4.459	3.389
	(0.814)	(1.065)	(1.422)	(4.757)	(5.202)	(4.917)
Socio-econ variables	NO	YES	YES	YES	YES	YES
Fert Advise and distance to ag mkt	NO	NO	YES	YES	YES	YES
Environmental & soil quality variables	NO	NO	NO	YES	YES	YES
Agro-ecological dummies	NO	NO	NO	NO	NO	YES
Regional dummies	NO	NO	NO	NO	YES	NO
Number of unique observations	1,048	1,048	1,042	1,042	1,042	1,042
R-squared	0.033	0.037	0.123	0.134	0.135	0.135

Note: Robust standard errors clustered at Enumeration Area level in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; dependent variable, real price of fertilizer, and amount of land cultivated are transformed using inverse hyperbolic sine transformation. Fertilizer prices are adjusted to the average October to December 2015 national prices. The full regression results are presented in Table A2-3 in the Appendix.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Using the demand estimates presented in the last columns of Tables 2-7 and 2-8, consumer surplus from redeeming a fertilizer voucher— worth 50 kg bag of either NPK or urea in the FISP— is calculated for non-recipients. That is, I estimate the welfare gain that would have accrued to non-recipients of fertilizer vouchers had they been targeted by the program. As discussed earlier, this is similar to estimating the treatment effect for the untreated—the treatment being the subsidy program. The analysis is done using the 2016/17 round of the IHPS data. This surplus is calculated for each household depending on which fertilizer demand scenario, as illustrated in Figure 2-1, it falls under.

Table 2-9 below shows the distribution of voucher non-recipients over the five demand scenarios shown in Figure 2-1 and Tables 2-1 to 2-3. The results show that most of the non-recipients fall under the third case: 74.7 % for NPK and 70.6% for urea. This is followed by the fourth demand scenario with 17.9% and 24% of the voucher non-recipients belonging to the second demand scenario for NPK and urea fertilizer respectively. These results imply that at the subsidized price (P_s), most farmers would like to buy less than one bag (50kg) of fertilizer of either type. This is remarkable given that farmers are expected to pay only about 20% of the average value of the vouchers under the subsidy program. As discussed above, factors that determine the intercept term in the fertilizer demand function (i.e. $\alpha_j X_{ij}$) or "demand shifters" such as asset holdings and shrinking land size are likely to bind farmers' demand for chemical fertilizers.

Table 2-9: Number of Voucher Non-recipients in the Sample in Each Demand Category in 2016/17

Fertilizer Demand Scenarios	**NPK**	**Urea**
1: no demand at Ps	0	1
2: WTP for one bag < Ps < choke price <Pm	38	16
3: WTP for one bag < Ps <Pm < choke price	914	863
4: Ps < WTP for one bag <Pm	205	289
5: Pm < WTP for one bag (inframarginal)	66	54
Total	1223	1223

Note: P_m = farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer in 2016/17).
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Using the fertilizer demand estimates, I calculate the mean and median amount of subsidized fertilizer demanded by non-beneficiaries of the program at the subsidized price of 3,500 Kwachas per 50 kg bag (or 70 Kwachas/kg) of either fertilizer type. The results are shown in Table 2-10 for each fertilizer demand scenario.

Focusing on the third demand scenario, farmers demand only about 20 kg of NPK and 23 kg urea at the subsidized price. These results suggest that without addressing the binding constraints on increased fertilizer use, the current policy of requiring the purchase of 50 kg bag of fertilizer under FISP at the subsidized price is burdensome for many beneficiaries. This also creates an incentive to resell some of the subsidized fertilizer. In section 7.6, I consider the welfare implications of a more flexible packaging of the subsidized fertilizer with 20 kg bag of fertilizer on offer in addition to the 50 kg bag currently being sold. On the other hand, non-beneficiaries in the fourth fertilizer demand scenario—the scenario with the second largest number of non-beneficiaries— demand about 89 kg of NPK and 96.7 kg of urea on average at the subsidized price.

Table 2-10: Amount of NPK and Urea (kg) Demanded by Voucher Non-recipients at Subsidized Price in 2016/17

	NPK		Urea	
Fertilizer demand scenarios	**Mean**	**Median**	**Mean**	**Median**
1: no demand at Ps	0.00	0.00	0.00	0.00
2: WTP for one bag < Ps < choke price <Pm	3.00	2.98	3.07	3.21
3: WTP for one bag < Ps <Pm < choke price	20.30	17.55	23.04	21.56
4: Ps < WTP for one bag <Pm	89.83	75.85	98.80	84.52
5: Pm < WTP for one bag (inframarginal)	332.40	292.35	328.11	324.33

Note: P_m = farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer in 2016/17)
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

2.7.2. Matching Fertilizer Voucher Non-recipients with Recipients

As outlined in Section 5, the next step in the analysis is to match non-recipients with recipients of the vouchers. Households with similar probability of being targeted by FISP are expected to be similar in important determinants of fertilizer demand reported so far. Indeed, this is true on observable characteristics as will be discussed below. Thus, matching recipients with non-recipients on observable characteristics helps alleviate selection bias inherent in the nonrandom targeting of the program. Nearest neighbor propensity score matching with replacement is employed to accomplish this. Table 2-11 presents probit marginal estimates of the probability of receiving fertilizer vouchers. The actual regression controls for many more potential determinants of receiving fertilizer vouchers. In Table 2-12, I present the results from the balance test or difference-of-means test on important variables between matched voucher recipients and non-recipients.

The results in Table 2-11 show that households with more asset holdings and access to basic services, that cultivate larger amount of land, with female heads and lower education level, are more likely to be targeted by FISP. As expected from Table 2-4, the results also show that being networked with the village head or traditional authority is the strongest predictor of receiving the vouchers. This is perhaps because, as noted by Chirwa and Dorward (2013), the program historically gave village heads a strong say in the targeting and redistribution of the vouchers. Thus, being closely linked with the village head affords a better chance to obtain the fertilizer vouchers even after controlling for other factors such as wealth and land size.

Table 2-11: Marginal Probit Estimates of the Probability of Receiving Fertilizer Vouchers in 2016/17

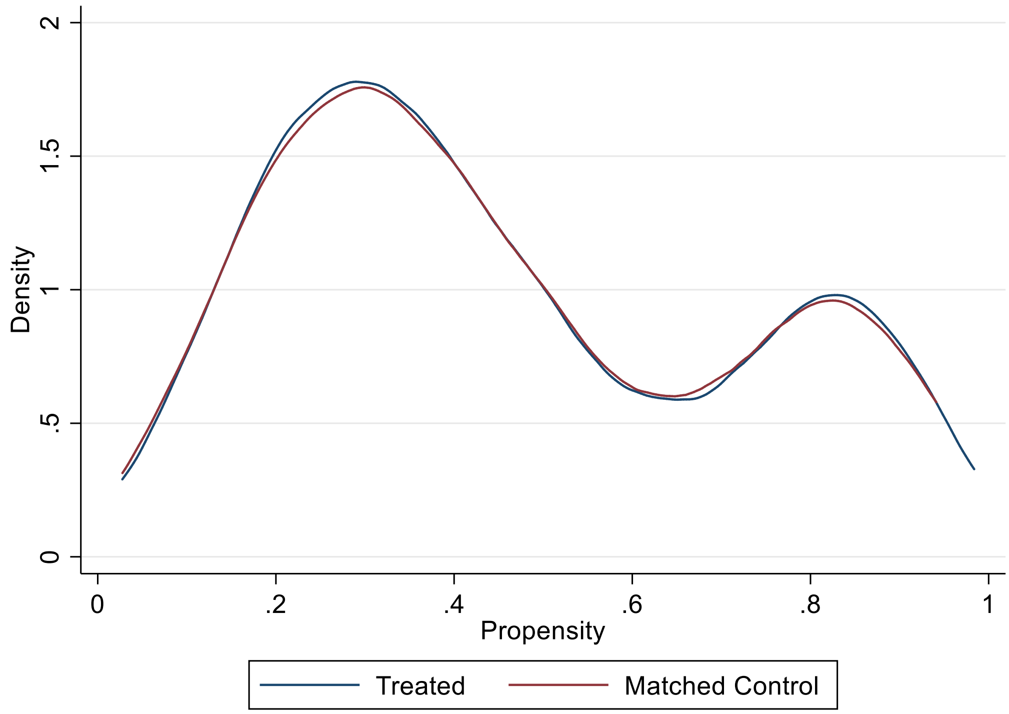
Variables	**Coeff (S.E)**
Wealth Index	0.013*** (0.004)
Log (land size cultivated by the household in ha)	0.140*** (0.022)
Farm credit org in village (=1 if yes)	-0.006 (0.021)
HH size (adult equivalent)	-0.005 (0.005)
Female headed HH (=1 if female)	0.052** (0.023)
Age of HH head	0.001 (0.001)
Years of education for HH head	-0.006** (0.003)
Networked with village head (=1 if yes)	0.374*** (0.026)
Other Controls	Yes

Note: Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Soil quality and agroecological dummies are included in the regressions but have been omitted from the table for ease of presentation; The base group for the soil attributes is "severe or very severe problem." Dependent variable: whether HH received fertilizer voucher (=1 if yes)
Source: Author's analysis from IHPS data for Malawi collected in 2016/17.

Using these probit estimates, propensity scores or probabilities of receiving the vouchers were calculated for all households in the IHPS 2016/17 data. Recipients and non-recipients of the vouchers are then matched using nearest neighbor matching method. The mean absolute difference in propensity scores is just 0.0015. This shows very close matches between households in the program with those who did not receive the vouchers. In addition to this absolute difference, Figure 2-4 shows the distribution of propensity scores between FISP voucher recipients and their matched counterparts among non-recipients. It shows very strong overlap in the probability of receiving

FISP vouchers between the two groups. Also, about 92.6% of voucher recipients and 87.5% of non-recipients in the sample satisfy the common support condition resulting in very limited exclusion of households in the matching process.

Figure 2-4: Kernel Density of Propensity Scores for FISP Voucher Recipients and Their Matched Counterparts Among Non-recipients in 2016/17



Note: The percentage of households with common support are 92.6% for voucher recipients and 87.5% for voucher non-recipients.
Source: Author's analysis from IHPS data for Malawi collected in 2016/17.

In addition to the matching exercise, the results from the balance test between matched voucher recipients and non-recipients are presented in Table 2-12. It shows that, on average, the two groups are very similar in observable characteristics. Importantly, this is also true among important determinants of fertilizer demand presented in Tables 2-7 and 2-8 (or Tables A2-2 and A2-3 in the appendix).

Table 2-12: Balance or Difference of Means Test Between Matched Voucher Recipients and Non-recipients in 2016/17

Variables	Voucher non-recipients	Voucher recipients	|t test| diff of means
Log (land size cultivated by the household in ha)	0.72	0.76	-0.04
Wealth Index	0.58	0.75	-0.17
Farm credit org in village (=1 if yes)	0.43	0.45	-0.02
HH size (adult equivalent)	4.52	4.39	0.13
Female headed HH (=1 if female)	0.29	0.28	0.01
Age of HH head	47.96	49.13	-1.17
Years of education for HH head	4.99	4.57	0.42*
Networked with village head (=1 if yes)	0.3	0.25	0.05
HH received assistance through safety net (=1 if yes)	0.42	0.4	0.02
Log (KM from HH to nearest agricultural market)	3.08	3.11	-0.03
Log (elevation in meters)	6.75	6.73	0.02
Log (annual precipitation in mm)	6.5	6.5	0
Soil quality index	0.03	0.11	-0.08
HH experienced irregular rain (=1 if yes)	0.75	0.79	-0.04

Source: Author's analysis from IHPS data for Malawi collected in 2016/17.

To get an idea of what percentage of FISP households engage in reselling of fertilizers in my estimates, in Table 2-13 I present the demand scenarios that voucher recipients fall under after matching. The results show that 60% of NPK and 46.6% of urea buyers among voucher recipients fall under the third demand scenario. These percentages are lower than those presented in Table 2-9 as voucher recipients tend to be wealthier and cultivate more land than voucher non-recipients (see Tables 2-4 and 2-5). As a result, there are more FISP farmers (in percentage terms) that demand more than the 50 kg fertilizer at the subsidized price (i.e. those that belong in fertilizer demand scenarios 4 and 5). These results suggest that there is strong incentive for many FISP farmers to engage in the secondary fertilizer market—both by reselling or buying the program fertilizer—absent the restrictions on the activity.

Table 2-13: Number of Voucher Recipients in Each Demand Category After Matching in 2016/17

Fertilizer Demand Scenarios	NPK	Urea
1: no demand at Ps	0	0
2: WTP for one bag < Ps < choke price <Pm	5	1
3: WTP for one bag < Ps <Pm < choke price	279	221
4: Ps < WTP for one bag <Pm	141	196
5: Pm < WTP for one bag (inframarginal)	49	56
Total	474	474

Note: P_m = farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer).
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

2.7.3. Welfare Estimates

I am now able to estimate the consumer surplus for recipients, which is equal to the welfare gain that their matched non-recipients would have gotten had they received the vouchers. These welfare estimates were calculated as was done in Tables 2-2 and 2-3, and they vary according to the fertilizer demand scenario and the fertilizer resell regime.

Table 2-14 presents descriptive statistics for the estimated consumer surplus (in MK) among FISP beneficiaries from redemption of vouchers for 50 kg bag of fertilizer in 2016/17. The results show that, without the fertilizer resell option, beneficiaries of the FISP program received about 11,000 MK worth of benefits on average from the subsidized fertilizers for both types of fertilizer. The corresponding values for the 20th percentile and 80th percentile of the consumer surplus or benefits distribution are at 3,581 MK and 17,921.7 MK, respectively.

When FISP households can buy or sell at the secondary market for the program fertilizer, the welfare estimates calculated in this section rely on the crucial assumption that the extra-demand for subsidized fertilizer by voucher recipients at the subsidized price (70 MK/kg) and median resell price (177.1 MK/kg) is met at this market. In addition to this, voucher recipients who would like to resell some or all of their subsidized fertilizer at these prices are able to do so.[8]

[8] These two assumptions work when beneficiaries in the bottom three fertilizer demand scenarios first sell some or all of their subsidized fertilizer to voucher recipients in the fourth or fifth demand scenarios

As expected, when FISP households engage in the secondary market for the program fertilizer, the benefits are larger than without this option. More specifically, when beneficiaries who belong to the second and third demand scenarios engage in resell of some of their program fertilizer at the subsidized price (i.e. at P_s value of 70 MK/kg) to those in the fourth and fifth demand scenarios (and potentially even to non-FISP farmers), essentially sharing the benefits with them, the average benefit to FISP households increases to about 18,689 MK nationally. The spread of benefit is larger for this scenario, with beneficiaries in the 20th, 50th, and 80th percentiles getting about 4,558 MK, 11,982 MK, and 27,008 MK from the fertilizer vouchers, respectively.

When most beneficiary farmers engage in either reselling or buying of the program fertilizer from the secondary market at the median resell price estimated from the literature (i.e. at P'_m=177.1 MK/kg), the mean and median benefits become 13,969.3 MK and 12,433.2 MK respectively. The corresponding benefits at the 20th and 80th percentiles are at 6,546.3 MK and 19,610 MK respectively.

Table 2-14: Descriptive Statistics on Consumer Surplus (in MK) from Redemption of Vouchers for 50 kg Fertilizer (with and without resell option) under FISP in 2016/17

Fertilizer resell regime	Mean	Median	20th percentile	80th percentile	Standard Deviation
Without resell option	10,996.9	10,412.7	3,581.0	17,921.7	7,782.5
With fertilizer resell at P_s	18,689.0	11,982.4	4,557.6	27,008.3	20,202.1
With fertilizer resell at P'_m	13,969.3	12,433.2	6,546.3	19,609.9	6,733.9

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

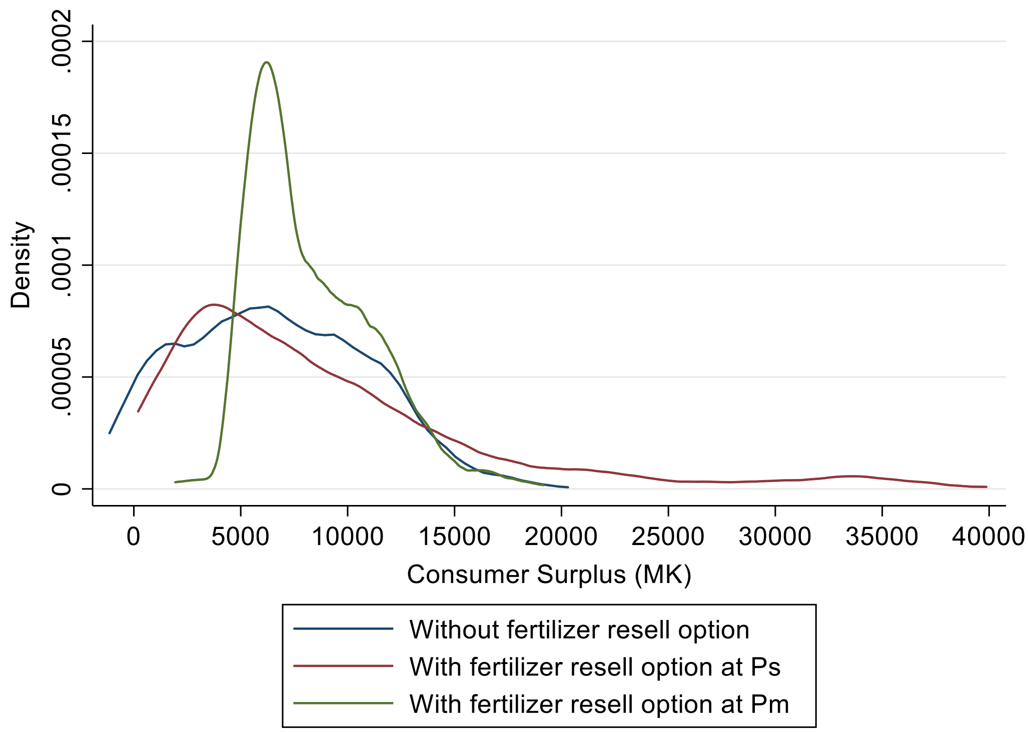
Comparing the two fertilizer resell regimes, beneficiaries who were at the bottom 20th percentile in benefits increase their benefits when they resell at the higher resell price than at the subsidized price. The opposite is true for FISP households that received relatively large benefits from the program. This is intuitive since when FISP households in the bottom of the benefits distribution are engaged in reselling of the fertilizer at lower price, they get lower benefits compared to reselling at higher prices. On the other hand, relatively liquidity unconstrained beneficiary farmers that buy from these farmers—in addition to the 50 kg that they received through FISP—derive higher

(see Figure 1). Extra-supply of fertilizer at the subsidized or median resell price, if any, are then made available to voucher non-recipients.

benefits from buying at lower prices. The distributions of benefits also show that FISP households are better off with the option to engage in the secondary market than without.

Figure 2-5 shows the kernel density distribution of consumer surplus or benefits for each of the three fertilizer resell regimes. As might be expected from Table 2-14, the distribution of benefits is more concentrated without the fertilizer resell option or with a resell at the median resell price than with the resell price at the subsidized or breakeven price. Beneficiaries in demand scenarios 4 and 5 achieve relatively high benefits from buying at the subsidized price since they demand more than 50 kg of fertilizer at the subsidized price (see Table 2-10). On the other hand, many beneficiary farmers resell a substantial portion of their subsidized fertilizer at the median resell price and get similar benefits. On the other hand, FISP households in higher demand scenarios buy smaller amounts of fertilizer from the secondary market at the median resell price. These two effects contribute to the concentration of benefits around the mean for the third fertilizer resell regime. When farmers have no option to resell the program fertilizer, some decide not to redeem their vouchers as shown in the distribution around zero benefits. Others redeem the vouchers but incur the cost of not be able to resell it in the secondary market. Relatively well-off beneficiaries are also restricted to buying only the 50 kg fertilizer at the subsidized price even though they have much higher demand at this price. Thus, the benefits are less dispersed than under the second fertilizer resell regime.

Figure 2-5: Kernel Distribution of Consumer Surplus per Voucher for Different Fertilizer Resell Regimes in 2016/17



Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

2.7.4. Benefit-Cost Analysis

How does the benefit of subsidized fertilizer compare to the cost of the program? To answer this question, I estimate the benefit-cost ratio of the program. During the months that the IHPS data were collected in 2016 and 2017, throughout Malawi each fertilizer voucher was redeemable at 3,500 Kwachas per 50 kg of either NPK or urea. Chirwa et al (2016) use the national logistics data and estimate that about 62% of the total fertilizer under FISP was distributed through government parastatals at the average cost of 20,683 MK/bag while the remaining 38% of the fertilizer was delivered through the private sector at an average cost about 18,000 MK/bag in the 2015/16 planting season. The weighted national average value of the voucher is thus 19,677 MK per 50 kg bag. This means that the FISP covers 16,177 Kwachas or about 82% of the average value of the voucher. To calculate the aggregate cost of the program, each redeemed voucher in the survey was multiplied by 16,177 and weighted by the sample weights to provide a rough estimate of the cost.

However, note that the cost to the government of each redeemed voucher is likely to differ by location. For example, the cost of delivering fertilizer in remote areas is likely to be higher than the cost of distribution near urban centers. In the absence of location specific data on the cost of the program, the national average cost of the vouchers is used.

Table 2-15 shows aggregate benefits, program costs, and benefit-to-cost ratios of the FISP program.[9] The results show that the program has resulted in low benefits compared to the costs of the program. This is especially true when beneficiary farmers do not engage in resell of fertilizers or do so at the median resell price. At the national level, each MK spent for subsidizing fertilizer yielded a benefit of only 0.43 MK to beneficiary households without the fertilizer resell option. This increases to 0.66 MK when farmers have the option to resell at the subsidized price. The benefit-to-cost ratio becomes 0.49 when farmers can resell at the median resell price estimated from the literature.

Low benefits relative to costs associated with FISP are not new to the literature. Ricker-Gilbert (2014), for example, found that a 10 kg increase in the average amount of subsidized fertilizer acquired per household in Malawi led to only US $1.40 per year increase in average household income. Jayne et al. (2013) reported a financial benefit-cost ratio of 0.435 in 2009/10 for Malawi by dividing value of incremental maize output due to the program with total government program costs and incremental farmer costs. Using a new approach, this paper, along with Jacoby (2016), confirm the finding.

What explains such low benefit-to-cost ratios? As can be seen from the previous section, even with highly subsidized prices of fertilizer—farmers are expected to pay only about 20% of the average value of the fertilizers— most farmers' willingness-to-pay to redeem 50 kg of fertilizer is lower than the subsidized price (see Table 2-13). One important explanation could be lack of liquidity among beneficiary farmers. The fact that the value of asset holdings and access to basic services is an important determinant of fertilizer demand in in Tables 2-7 and 2-8 suggests that farmers may be credit constrained arising from shortages in collateral.

In addition to liquidity problems, lack of complementary investments in agriculture such as roads, irrigation, extension services, and crop insurance, may also explain the low benefit-to-cost ratios (Matchaya et al. 2014). Another explanation could be late delivery of subsidized fertilizer to

[9] Note that the benefit here accounts for the welfare gain derived by only beneficiary farmers. It does not, for example, account for consumer benefits from the program.

beneficiaries, a common feature of the subsidy program mentioned in the literature (see for example Chirwa and Dorward 2013). Research has shown that late application of nitrogen during the planting season could result in reduced crop yield due to nitrogen deficiency (Walsh 2006). Therefore, the welfare gain from subsidized fertilizer will be adversely affected by late delivery.

Table 2-15: Aggregate Consumer Surplus (billions of MK), Program Cost (billions of MK), and Benefit-Cost Ratios of FISP Beneficiaries in 2016

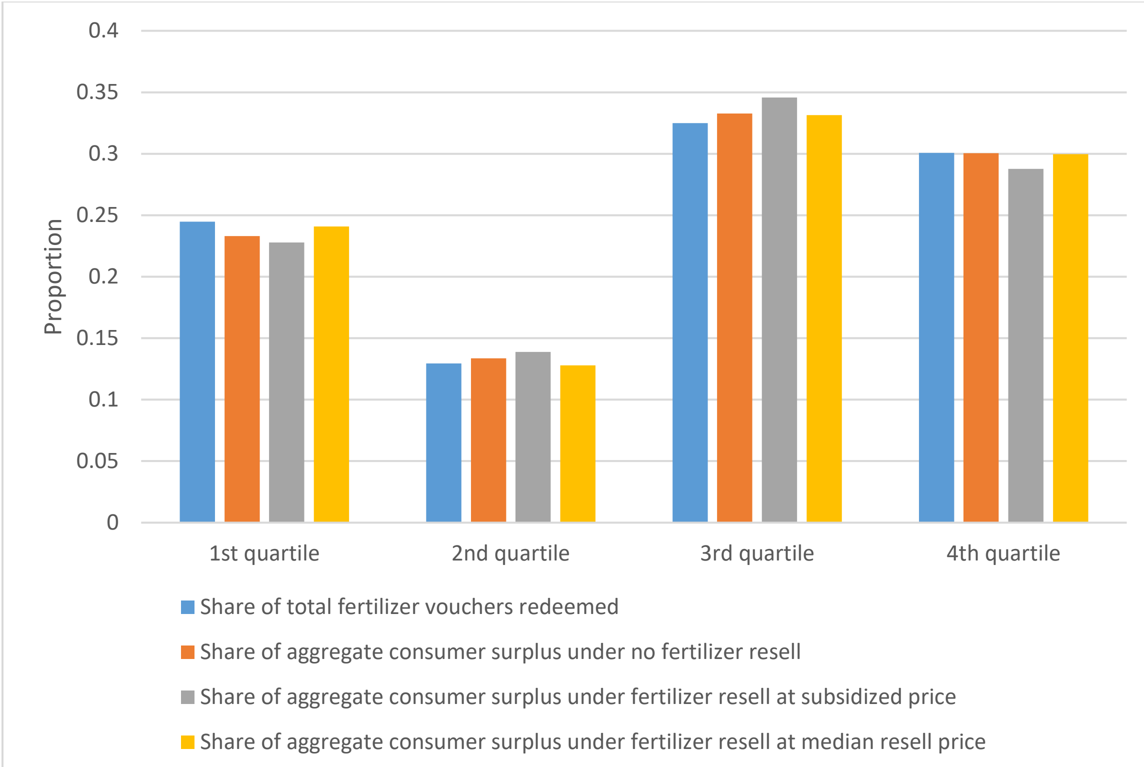
Fertilizer resell regime	Net consumer surplus	Cost of program	Benefit/Cost
Without resell option	60.67	139.79	0.43
With fertilizer resell at P_s	103.77	157.96	0.66
With fertilizer resell at P'_m	77.1	158.25	0.49

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

2.7.5. Distribution of Vouchers and Benefits

In this section, I investigate further the pro-poor nature of the FISP, which is one of the core objectives of the program. Figure 2-6 shows the distribution of total fertilizer vouchers and derived benefits (or net consumer surplus) by quartiles of wealth. Agricultural households in the bottom two quartiles received only 37.4% of the total available fertilizer vouchers. These households also received about 37% of the benefits with and without the fertilizer resell options. This is in direct contrast to the objectives of the FISP, which prioritize targeting poor smallholder farmers with fertilizer vouchers. Given that FISP covered about only twenty percent of all Malawian farmers in the 2015/16 planting season, one would expect from a well-targeted program the share of the coupons and benefits to be concentrated among the bottom wealth quartiles. This is not the case for the FISP.

Figure 2-6: Distribution of the Share of Redeemed Fertilizer Coupons and Aggregate Consumer Surplus Over Wealth Quartiles in 2016/17



Note: The wealth quartiles are calculated nationally after combining fertilizer voucher recipients and non-recipients. The 1st quartile includes households in the bottom 25% of the wealth index value. Similarly, households in the 2nd quartile (between 25% and 50%), 3rd quartile (between 50% and 75%), and 4th quartile (between 75% and 100%) in national wealth index value distribution.
Source: Author's calculations using IHPS data for Malawi collected in 2013 and 2016/17.

2.7.6. Welfare Implications Under Flexible Redemption of Fertilizer Vouchers

As already discussed in the previous sections, in the 2015/16 planting season, the majority of farmers in Malawi demanded less than 50 kg of fertilizer even at the highly subsidized price of 3,500 Kwachas per bag that is currently on offer under the FISP. As the regression results show, liquidity problems and small farm size are binding constraints to increasing farmers' usage of chemical fertilizer. Under the FISP, fertilizer vouchers are redeemable for only 50 kg bag of either fertilizer type. In this section, I present the welfare implications if the vouchers are redeemable for either 50 kg or 20 kg bag of NPK or urea fertilizer. This way, the household with the voucher for an NPK fertilizer will have the two options of redemption available from which they must choose one. The same approach works for urea vouchers. The additional option to redeem the 20 kg fertilizer is chosen because the weighted average of the amount of fertilizer demanded at the subsidized price for the second and third demand scenarios are about 20 kg. Thus, this additional option is included to reflect the low demand for fertilizer at the subsidized price by many beneficiary farmers (see Tables 2-10 and 2-13).

In this regime, there would be four possible options for redemption of the two vouchers distributed under FISP for NPK and urea fertilizers. These include: 1) 50 kg bag of both types of fertilizer (the current approach); 2) 20 kg bag of both types of fertilizer; 3) 20 kg bag of NPK and 50 kg bag of urea; and 4) 20 kg bag of urea and 50 kg bag of NPK.

In this flexible redemption approach, beneficiaries are assumed to choose the option that gives them the highest combined net consumer surplus. Practically, the net consumer surplus is calculated for each of the above options that could potentially be chosen by the FISP households. The net surplus with the maximum value is then applied to the beneficiary farmer. Note also that beneficiaries' cost of purchasing the 50 kg or 20 kg bag of fertilizer through the program are at 3,500 MK and 1,400 MK respectively—the 70 MK/kg cost remains constant. Maintaining beneficiaries' contribution at 1,400 MK per 20 bag is likely more burdensome for the government than charging the corresponding 3,500 MK per 50 kg bag.

I also assume that the public cost of distributing 20 kg fertilizer bags is 40 percent of dispersing 50 kg fertilizer bags under FISP. This is likely to be a lower bound of the public cost due to some fixed costs that must be incurred regardless of which fertilizer bag is distributed. That is, for example, the government will need to pay for the largely fixed cost of transporting the bags to different parts of the country and pay employees engaged in the distribution of the subsidized bags regardless of the size of the bags.

The distribution of consumer surplus (in MK) achievable under the flexible approach is presented in Table 2-16. Nationally, without the fertilizer resell option, the average benefit from flexible packaging of fertilizer bags is around 11,370 MK. This represents about a 3.4% increase from the status quo of just 50 kg redemption. However, for beneficiaries at the bottom 20th percentile in the benefit distribution, their benefits increase by about 18.6% with the additional option to buy the 20 kg bags but without the resell option. On the other hand, beneficiaries at the top 20th percentile practically do not benefit from this flexible packaging of the fertilizer. These results are intuitive in that FISP households who demand significantly less than 50 kg of fertilizer at the subsidized price—those in the first three fertilizer demand scenarios in Table 2-13—gain the most from this flexible redemption of fertilizer with the option to buy just 20 kg bag of fertilizer.

When FISP households can engage in the secondary market by selling or buying the program fertilizer, the advantage of flexible redemption vanishes (Table 2-16). This is because the secondary market for the subsidized fertilizer already provides farmers with the flexibility they need.

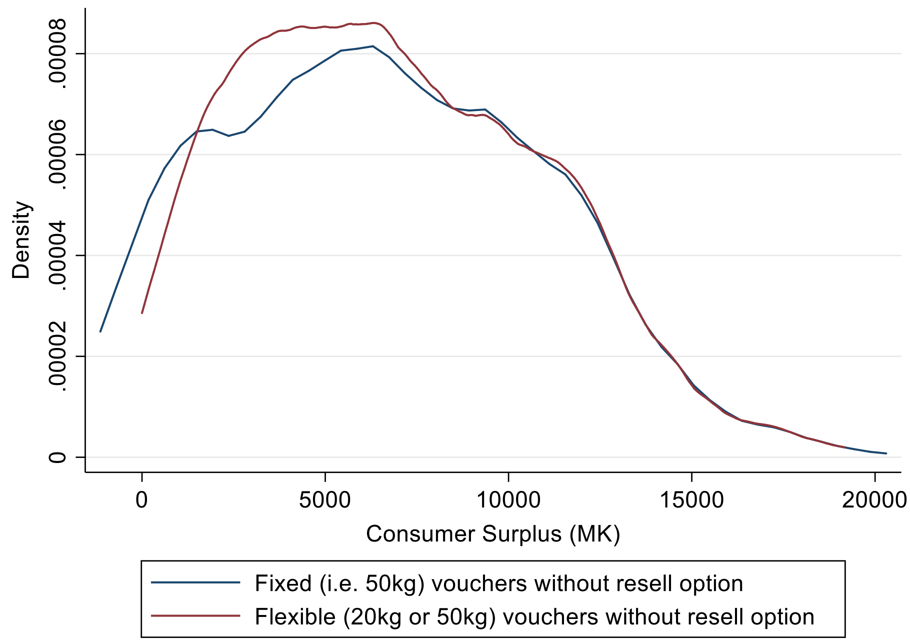
Table 2-16: Distribution of Consumer Surplus in MK from Redemption of Vouchers for either 50 kg or 20 kg Fertilizer

	Without resell option		With fertilizer resell at P_s		With fertilizer resell at P'_m	
Statistics	**Value**	**% change from status quo**	**Value**	**% change from status quo**	**Value**	**% change from status quo**
Mean	11,370.0	3.4	18,689.0	0.0	13,969.3	0.0
Median	10649.4	2.3	11982.4	0.0	12433.2	0.0
20th percentile	4246.0	18.6	4557.6	0.0	6546.3	0.0
80th percentile	18120.7	1.1	27008.3	0.0	19609.9	0.0

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Figure 2-7 presents the kernel distribution of consumer surplus with both fixed and flexible redemption of fertilizer vouchers when the secondary fertilizer market does not exist. As expected from Table 2-16, the benefits at the bottom quarter or so of the distribution shifts to the right when the regime changes from fixed to flexible redemption of fertilizer vouchers. These are households who tend to be poorer and cultivate smaller amounts of land. On the other hand, as the benefits from the 50 kg vouchers increase, the option value of flexible redemption decreases as farmers rarely choose the 20 kg bags. Thus, the distributions start to overlap at or above 9,000 MK in benefits per voucher.

Figure 2-7: Kernel Distribution of Consumer Surplus per Voucher for Fixed Redemption (50 kg fertilizer bags) and Flexible Redemption (20 kg or 50 kg bags) of FISP Vouchers Without Fertilizer Resell Option in 2016/17



Source: Author’s analysis from IHPS data for Malawi collected in 2013 and 2016/17.

The advantages of flexible packaging of fertilizer under the FISP considered in this section go beyond increased consumer surplus when farmers do not resell their subsidized fertilizer. If properly administered, it can also reduce the public cost of the program. As farmers are not required to redeem their vouchers for just 50 kg fertilizer, the government can save money by providing 20 kg fertilizers for farmers that find this option more profitable when restrictions on resell of program fertilizer are in place.

Table 2-17 shows the aggregate national benefits, public costs, and benefit-to-cost ratios associated with flexible redemption of vouchers. The public costs are, indeed, smaller and the benefit-to-ratios higher under the flexible approach than the current policy of fixing the redemption of vouchers at 50 kg fertilizer bags (compare Table 2-17 with Tables 2-15). This is achievable mainly through reduced cost to the government from selling the 20 kg bags through FISP. This also means there would be fewer opportunities for leakages to direct non-beneficiaries of the program from selling large unwanted amounts of fertilizer in the secondary market.

Table 2-17: Aggregate Consumer Surplus (billions of MK), Program Cost (billions of MK), and Benefit-Cost Ratios for FISP Beneficiaries from Redeeming Vouchers for either 20 kg or 50 kg bag Fertilizer in 2016/17

Fertilizer resell regime	Consumer surplus	Cost of program	Benefit/Cost
Without resell option	61.95	123.25	0.50
With fertilizer resell at P_s	103.77	64.26	1.61
With fertilizer resell at P'_m	75.94	157.36	0.48

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

In addition to the flexible redemption approach, I have also calculated the welfare benefits and public costs of voucher redemption of only 20 kg of NPK and urea fertilizer instead of the current redemption of 50 kg of fertilizer. The results are reported in Tables A2-5 and A2-6 in the appendix. Nationally, the average surplus from redeeming vouchers for 20 kg fertilizer bags with restrictions on resell of fertilizer is 37.4% lower than the current approach. Thus, on average, the current policy of redeeming vouchers for 50 kg fertilizer is more preferable to beneficiaries than more than halving the subsidized fertilizer. Only households in the bottom of the benefits distribution seem to gain from moving entirely to redemption of vouchers for 20 kg bags when beneficiaries do not have the option to resell or buy the program fertilizer (Table A2-5). These results confirm the previous analysis in that flexible redemption of vouchers as configured here seems to benefit only poorer households. Of course, if there were more options for redemption of vouchers such as for 80 kg bags, it will increase farmers' benefits. Note from Table A2-5 that the benefit-to-cost ratios are significantly higher under 20 kg fertilizer redemption regime than the current policy regardless of the resell options demand. Thus, the reduction in public costs of the program more than outweighs the decrease in consumer surplus by moving from 50 kg to 20 kg redemption of vouchers.

2.7.7. Robustness Checks

I check for the robustness of the welfare estimates by allowing for a more flexible function of the fertilizer demand equation described in equation (2). To achieve this, I interact the amount of cultivated land with the soil quality index. This index was constructed from six other soil quality variables. I also include both linear and quadratic variables that are time-varying including the number of working age members, the age of the household head, and the amount of annual precipitation received in the previous season.

The resulting fertilizer demand estimates are reported in Table A2-4 in the appendix. The coefficients on the demand estimates including for price of fertilizer, amount of cultivated land and other variables are quite similar between those reported in Table A2-4 and Tables 2-7 and 2-8. As a result, the welfare estimates based on the flexible fertilizer demand equation are expected to be similar.

The subsequent robustness checks on welfare estimates based on fertilizer demand estimates in Table A2-4 are presented in Tables A2-6 to A2-15 and Figures A2-1 to A2-3 in the appendix. The distribution of voucher non-recipients and recipients over different fertilizer demand scenarios (Tables A2-7 and A2-9), amount of fertilizer demanded at the subsidized price (Table A2-8), descriptive statistics on consumer surplus attained by beneficiaries (Table A2-10), and aggregate consumer surplus, program cost, and benefit-to-cost ratios (Table A2-11) associated with current FISP policies are all very similar in magnitudes to the results reported in the previous sections.

The mean and median consumer surplus from redemption of 50 kg fertilizers under FISP calculated from the demand estimates in Table A2-4 are less than three percent different from their counterparts calculated from the demand estimates in Tables 2-7 and 2-8 (compare Table A2-10 with Table 2-14). This is true for any of the fertilizer resell regimes. More generally, the kernel distribution of consumer surplus per voucher presented in Figure A2-1 is quite similar to Figure 2-4.

Because of these small differences in benefits, the benefit-to-cost ratios (BCRs) calculated as robustness checks are also very similar with the main results reported thus far (compare Table A2-11 with Table 2-15).

Overall, the direct welfare implications of the current approach to subsidizing fertilizer in Malawi are stable for different regression specifications considered in this study. Similar observations can also be made with welfare estimates of alternative policies such as flexible redemption of fertilizer vouchers (compare Tables 2-17 to 2-19 with Tables A2-12 to A2-13; Figure 2-6 with Figure A2-3), moving to voucher redemptions of only 20 kg fertilizer bags (compare Tables A2-5 to A2-6 with Tables A2-14 to Tables A2-15), and distribution of benefits by wealth quartiles (compare Figure 2-5 with Figure A2-2).

2.8. Conclusion and Policy Implication

This paper addresses important research and policy questions related to the welfare impact of agricultural input subsidies in the context of Malawi. In doing so, I contribute to the debate on FISP by employing a rarely applied method to evaluate the welfare implications of input subsidy programs. I find that the Farm Input Subsidy Program provides low direct benefits compared to the costs of the program. At the national level, each Malawian Kwacha spent for subsidizing fertilizer yielded a benefit of only about 0.43 Kwacha. This is for the scenario where beneficiary households have no option to engage in the secondary market for FISP fertilizer (i.e., without the option to resell or buy the program fertilizer from this market). With the option to participate in the secondary market, the benefit—cost ratio (BCR) increases to as much as 0.67. My findings also suggest that flexible redemption of fertilizer vouchers have substantial positive impact on farmers' welfare and reduces the public cost of the program when opportunities to engage in the secondary market for the program fertilizer are limited. For example, when farmers have the additional option to buy 20 kg bags of fertilizer as opposed to only the 50 kg bags currently being offered under FISP, their average benefits increase by about 18.6% compared to the status quo for those famers that demand 20 kg of fertilizer or less at the subsidized price.

The findings in this paper are suggestive of several important policy implications. First, in order to make the input subsidy program successful, complementary investments such as access to credit, roads, irrigation, extension, crop insurance, and extension may be needed to increase farmers' effective demand for fertilizer. Second, the gap between the stated objectives of the program and implementation with regards to pro-poor targeting of the subsidized inputs should be narrowed. The recent move towards central targeting of the program should implement means testing to be eligible for the program. Third, the fertilizer bags under FISP may need to come with more options than just the 50 kg bags. This may help reduce side-selling of the fertilizer if a mechanism can be developed that matches farmers' needs with the program fertilizer they can get. Fourth, given the low benefit-to-cost ratios of the FISP but the huge opportunity cost of sustaining the program, the benefits of the program should be weighed against other social protection programs such as cash transfers. The program benefits should also be continuously compared with the benefits of scaling-up alternative public investments such as in agricultural research and development, extension services, and improving rural infrastructure.

Finally, any effort to amend the design or implementation of FISP should take the politics around the program into consideration. Dionne and Horowitz (2013), for example, find that the farm subsidy program in Malawi increased support for the ruling party by an estimated 6.2% - 7.2% from 2008 to 2010. Similarly, Mason and Ricker-Gilbert (2013) show that households in districts where the ruling party won in the previous presidential election were more likely to acquire subsidized seed and fertilizer. These findings suggest that a prerequisite to revamping or replacing the input subsidy program in Malawi with other alternatives is creating the political will to do so.

3. Crop Diversification, Poverty, and Shocks in Malawi

Habtamu Fuje[*] and Sinafikeh Gemessa[+]

3.1. Introduction

Malawi's agricultural sector contributes more than a quarter of the country's gross domestic product (GDP) and more than three-quarters of employment (Benson, Erman, and Baulch 2018). Unfortunately, the sector has also been beset by recurring natural shocks. For example, real agricultural GDP has contracted by 2.3 percent due to the widespread flooding in 2015 and by another 2 percent from the droughts in 2016. Most recently, tropical cyclone Idai caused major damages to life, crops, and physical assets in three southern African countries including Malawi. The human toll of these disasters is very high. The 2015 flooding, for example, was one of the worst in decades, and it affected 1.1 million people and destroyed infrastructure in 15 districts in Malawi (PDNA 2017; World Bank 2016). This trend is particularly troubling as the vast majority of the poor and vulnerable Malawians reside in rural areas (World Bank 2018a).

Malawi's agriculture is highly dependent on a few commodities with maize as the staple crop and tobacco for export. This has broader implications on the macroeconomy, agricultural productivity, soil nutrient content, and vulnerability to single crop failure. Indeed, the World Bank's recent Systematic Country Diagnostic (SCD) has identified lack of crop diversification as a major bottleneck to increasing agricultural productivity in Malawi (World Bank 2018b). The country's slow increase in agricultural productivity will likely further exacerbate rural poverty, particularly because the consumption of own maize production is very high.

Recent evidences suggest that some crop diversification into legumes and nuts has taken place, and diversification is associated with improved welfare. A study of irrigated cropland found that subsistence farmers who were producing two crops earned, on average, more than those producing only one crop (IFPRI 2014). Although a potential pathway out of poverty for smallholders is to earn greater returns by diversifying into higher-value crops, this option may be limited by factors

[*] Economist, World Bank, hfuje@worldbank.org
[+] PhD Candidate, University of Minnesota, sinafikeh@gmail.com

such as small plot sizes and high price volatility, which increase the incentives of households to revert to self-provisioning food staples (Chirwa 2010).

Smallholders in developing countries such as Malawi have often relied on intercropping as a risk reduction strategy from environmental stressors such as droughts and crop diseases. This is because some crops are more resilient to natural shocks than others and help maintain soil moisture during drought periods while preventing soil erosion during flooding, thus building better resilience in the agricultural system (Lin 2011; Njeru 2013). Diversification in crop production can also lead to improved nutritional outcomes because of greater dietary diversity (Mazunda, Kankwamba, and Pauw 2015). Crop diversification also improves soil quality and leads to increased agricultural productivity (Bezner-Kerr et al. 2007; Bellora et al. 2017).

The purpose of this study is to provide detailed evidence on the extent of crop diversification in Malawi and its links to consumption, incidence of poverty, and crop shocks. Understanding these relationships is key to support farm households in their attempt to diversify away from maize, especially in the wake of the recent weather shocks and distortions to grain markets. More specifically, the study addresses the following policy-relevant questions: (a) What types of farm households are able to diversify their crop portfolios? The paper describes the type of farmers who are able to diversify and identify key factors that could be hindering or fostering their ability to engage in diversified farming. (b) What is the association between crop diversification and household consumption and with poverty reduction? A clear understanding of this association is an important first step before supporting crop diversification. (c) What is the relationship between crop diversification and experiencing crop shocks? Answering this last question will at least partially explain why farmers may be engaged in crop diversification. If there is, for example, a positive correlation between crop diversification and experience with crop shocks such as droughts and crop diseases, then this is suggestive evidence that farmers may use crop diversification as a coping mechanism to these shocks. Furthermore, resilience to crop shocks is better achieved through intercropping—in contrast to monocropping—due to crops' differing tolerance to stress factors such as droughts, diseases, and pests (Lin 2011; Njeru 2013). To properly address these key questions, we will control for some confounding variables including sociodemographic, geographic, and year fixed effects (FEs). However, due to data limitation issues, it is very difficult to establish definitively the causal link between crop shocks, crop diversification, and poverty.

Many recent studies have looked at crop diversification and its links to welfare outcomes in Malawi (see for example, Bezner-Kerr et al. 2007; Jones 2017; Jones, Shrinivas, and Bezner-Kerr 2014; Kankwamba, Kadzamira, and Pauw 2018; Koppmair, Kassie, and Qaim 2016; Mango et al. 2018; Mazunda, Kankwamba, and Pauw 2015; Snapp and Fisher 2015). Almost all these studies found positive association between diversification in crop production and some measure of welfare outcome(s) in Malawi. For example, Bezner-Kerr et al. (2007) found positive association between diversification into legume crops and improved child nutrition outcomes. Jones (2017) also found the same directional relationship between crop diversity and intake of both macronutrients (for example, calorie and protein) and micronutrients (for example, vitamins and minerals). In the same vein, Jones, Shrinivas, and Bezner-Kerr (2014), Mango et al. (2018), Mazunda, Kankwamba, and Pauw (2015), and Snapp and Fisher (2015) found farm production diversity to be consistently positively associated with dietary diversity. Mazunda, Kankwamba, and Pauw (2015) also found that crop diversification was positively associated with higher levels of education, larger landholdings, access to fertilizer, and market participation. Kankwamba, Kadzamira, and Pauw (2018) and Snapp and Fisher (2015) did not find evidence that participation in the large farm input subsidy program in Malawi precluded crop or dietary diversity. In fact, participation in the program improved both measures of diversity by helping beneficiary farmers to commercialize and get access to high-value seeds and food purchases. While Koppmair, Kassie, and Qaim (2016) also found that farm production diversity is positively associated with dietary diversity, their estimated effects were small. They found that better access to markets for buying food and selling farm produce and use of chemical fertilizers were more important for dietary diversity than diversity in farm production.

This study builds upon previous research by shedding light on the association between on-farm crop diversity and standard measures of welfare including total consumption and instances of poverty. While welfare outcomes such as dietary diversity, agricultural productivity, and education are important in themselves, they are only indirectly related to household consumption expenditure or incidences of poverty. This paper, therefore, provides evidence for the unmediated association between crop diversity and the commonly used welfare measures.

Beyond Malawi, other studies that have looked at farm production diversity and its links to welfare outcomes include Adaakohol and Aye (2014) in Nigeria, Bellora et al. (2017) in South Africa, Benin et al. (2004) in Ethiopia, Coelli and Fleming (2004) in Papua New Guinea, Islam and Ullah (2012) in Bangladesh, Makate et al. (2016) in Zimbabwe, M’Kaibi et al. (2017) in Kenya, Nguyen

(2017) in Vietnam, and Weigel et al. (2018) in Germany. Like the studies in Malawi, these studies found largely positive relationship between crop diversification and their measures of welfare (typically diet diversity or agricultural productivity).

The comprehensive Integrated Household Surveys (IHS) data are used for this study. The analysis uses the three waves of IHS data collected in 2004, 2010, and 2016. The data are representative at the national, regional, and district levels. Each round of survey has detailed household- and individual-level data on socioeconomic characteristics, agricultural and nonagricultural activities, consumption, assets, and other indicators.

We find that diversified households enjoy higher consumption and have a better chance of escaping poverty, and farmers exposed to shocks are more likely to diversify. Farm households that engage in crop diversification tend to have higher consumption levels. And crop diversification is positively correlated with higher probability of escaping poverty. The strong association between crop diversification and household consumption (and hence, low poverty) is stronger for households in the bottom four consumption quintiles. In addition, households that have experienced crop shocks are more likely to engage in crop diversification.

The rest of the paper is structured as follows. Section 2 presents the empirical approaches, including how crop diversification is measured and a detailed description of the estimation strategy used to address the key policy questions. Section 3 describes patterns of crop diversification, key factors that explain crop diversification, and their relationship with consumption and poverty. In Section 4, we discuss the policy implications of the findings from this study.

3.2. Empirical Strategy

3.2.1. Measuring Crop Diversification

To measure diversification, we start with a simple measure of counting the number of crops grown by farm households. Based on this, households are classified into those that grow only one crop (typically maize), two crops, and three or more crops. Even if this simple measure of crop diversification is a good starting point, it does not take into account the size of cultivated land nor the proportion of cultivated land covered by each crop. Therefore, we complement this with a widely used index to measure diversification.

Simpson’s diversity index (SDI), a more accurate measure of crop diversification that accounts for the share of area allocated to different crops as well as the evenness of this allocation, is utilized as an additional measure of diversification.

The SDI (Simpson 1949) for household *i* in year *t* (γ_{it}) is calculated as:

$$\gamma_{it} = 1 - \sum_{j=1}^{T} s_{ijt}^2, \qquad [1]$$

where *T* is the total number of cultivated crops, and s_{ijt} is the share of the cultivated area allocated to crop type *j* by household *i* in year *t*. The SDI takes values between 0 and 1, with 0 indicating monocropping and 1 implying infinite diversification. This index is extensively used to measure crop diversity in the literature (see Ecker 2018; Lim 2018; Magurran 2003; Malik and Nautiyal 2016; Sichoongwe et al. 2014).

3.2.2. Estimation Strategy

In addition to the rich descriptive analysis of crop diversification patterns among farm households, we conduct a regression analysis to identify factors that could be associated with diversification. The regressions include key household characteristics and agriculture indicators as well as district and year FEs to account for differences across districts and over time.

After identifying key drivers of diversification, we analyze the association between diversifications and household welfare. This is done by running a regression of real consumption per capita on indicators of diversification (the SDI or the number of crops planted by household), key household characteristics, as well as on district and year FEs. To understand the links between crop production diversification and consumption as well as between diversification and the incidence of poverty, the following equation adapted from Ecker (2018) is estimated:

$$Y_{it} = \alpha_0 + \beta\gamma_{it} + X_{it}'\theta + \varphi_t + \delta_d + \varepsilon_{it} \qquad [2]$$

where i indicates the household and t refers to the survey round or year of interview. *Y* refers to (log) consumption level or poverty status of the household. γ_{it} is the measure of crop diversification such as the SDI or the number of crops planted by household i in year *t*. X_{it}' includes a vector of socioeconomic characteristics including household size, and the household head's standard characteristics: sex, age, and the years of education. φ_t controls for year effects taken from round of the survey while δ_d captures district fixed effects. ε_{it} is the error term. α_0 is the constant term. β is the key coefficient to be estimated. The vector θ contains the coefficients on the controls. The standard errors will be clustered at the enumeration area level so that the independence of samples' assumption is relaxed within the clusters. Note that, when the dependent variable is consumption per capita Ordinary Least Squares (OLS) estimation is used. However, when poverty status (ultra-poor, moderately poor, and non-poor) is the dependent variable, ordered logit regression is estimated (Wooldridge 2010). Similarly, the association of diversification with poverty status (ultra-poor, moderately poor, or non-poor) is investigated using ordered logit regression.

Finally, we investigate one of the important mechanisms through which crop diversification influences welfare—its ability to ease crop losses arising from environmental stressors such as droughts and diseases. Compared to monocropping, multiple cropping is often less vulnerable to crop failure precipitated by environmental factors (Peter and Runge-Metzger 1994; Nhamo et al. 2014). Intercropping often insures against crop failure due to crops' differing tolerance to droughts and diseases, among others. On-farm crop genetic diversity can also reduce the need to apply harmful chemicals such as pesticides and herbicides in the presence of pest- and weed-resistant crop varieties (Crop Trust 2018). The association between diversification and crop loss is analyzed running a regression of diversification indicators on reported crop losses and other controls. Specifically, to analyze relationship between diversification and experience of crop production losses, the following reduced-form equation is estimated:

$$\gamma_{it} = \sigma_0 + \eta L_{it-1} + X'_{it}\lambda + \varphi_t + \delta_d + \mu_{it} \qquad [3]$$

where L captures whether the household experienced crop-loss due to droughts, disease, pests, or flood in the previous planting season.[10] μ_{it} represents the error term. The key coefficient is η that measures the correlation between crop diversification and crop-loss after controlling for other factors. We hypothesis η to be positive suggesting that farmers that experience crop shocks are likely to engage in crop diversification to mitigate the impact of the shock.

3.3. Diversification Pattern and its Links with Poverty and Shocks

3.3.1. Data

The results presented in this section are based on the cross-sectional IHS data. IHS is representative at the national, urban/rural, regional, and district levels. The data include detailed information about households' socioeconomic characteristics, agricultural and nonagricultural activities, consumption, and assets. The IHS waves were conducted in 2004/5, 2010/11, and 2016/17, and collected information from 12,447, 12,271, and 11,280 households, respectively.

3.3.2. Patters of Poverty in Malawi

Malawi made little progress when it comes to reducing poverty in the last two decades. According the IHS data, at the national level, the incidence of poverty only marginally decreased from 52.4%

[10] Farmers were asked whether they experienced any of these shocks in the last 12 months.

in 2004 to 51.5% in 2016 (Table 3-1). The incidence of ultra-poverty also decreased slowly (22.4% in 2004 Vs. 20.1% in 2016) while moderate poverty—those above the ultra-poverty line but below the poverty line—slightly increased over the same period (30% in 2004 Vs. 31.5% in 2016).

Table 3-1: Incidence of Poverty in Malawi (%)

Year	Poor	Ultra-poor	Moderately poor
2004	52.4	22.4	30.0
2010	50.5	24.4	26.1
2016	51.5	20.1	31.5

Source: Authors' calculation based on IHS 2-4.
Note: In IHS2 (2004/5), the poverty line was MKW 37,002 per year per person. This poverty line has been adjusted in IHS3 (2010/11) and IHS4 (2016/17) to reflect changes in cost of living. Those individuals with total expenditure below the amount needed to satisfy basic food needs are considered as ultra-poor. The ultra-poverty line in IHS2 was MKW 22,956 per year per person, and this has also been adjusted to reflect changes in living cost during IHS3 and IHS4 (World Bank 2018a).

3.3.3. Patterns of Crop Diversification

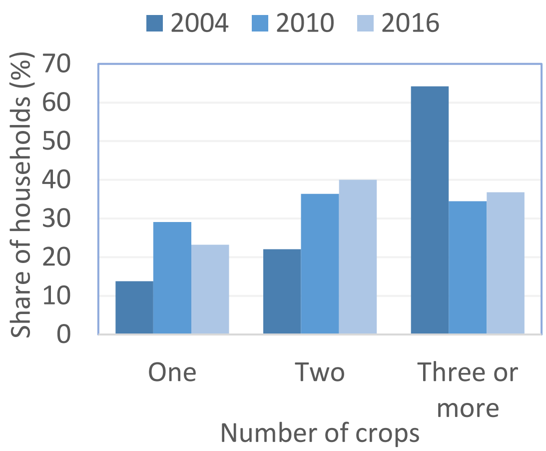
Reliance on maize as the single most important crop continues to be a noticeable feature of Malawi's agriculture. The share of farm households counting on just one crop as the source of their livelihoods increased from 14 percent in 2004 to 29 percent in 2010, before declining slightly to 23 percent in 2016. Even if the proportion of households growing two crops increased during 2004–2016, those with more diversified crop portfolio of three or more crops has substantially declined (Figure 3-1a).

Crop diversification has declined over time, and the average number of crops grown by farmers has declined from around three in 2004 to two in 2016. The SDI, which accounts for the number of crops as well as the share of each crop in the total cultivated land, has also declined between 2004 and 2016 (Figure 3-1b).

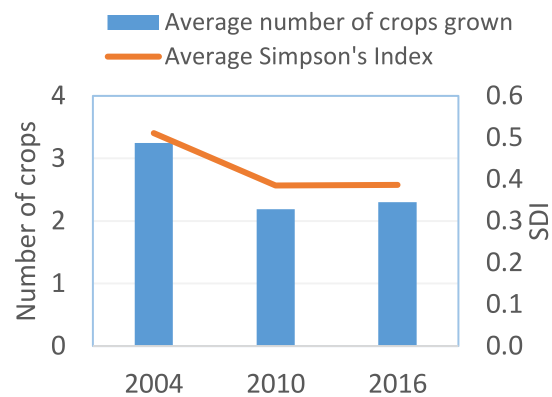
The level of crop diversification shows very little variation across the regions of Malawi. In each of the three regions, households that grow three or more crops are the largest group accounting for more than 40 percent of farmers. The average SDI is slightly higher in the southern region compared to the other regions (Figures 3-1c to 3-1d).

Figure 3- 1: Crop diversification has declined since 2004, and there is limited difference across regions

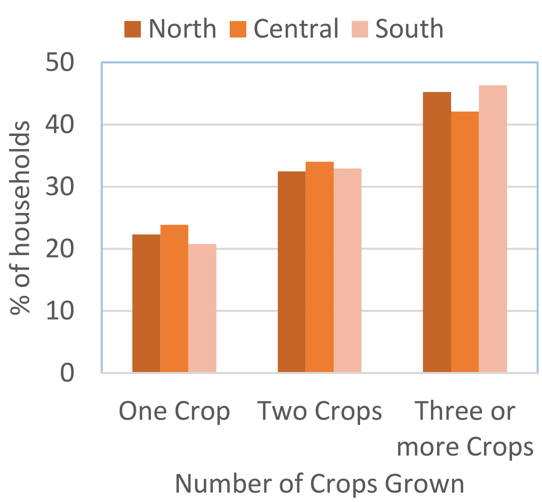
(a) Number of crops grown over time



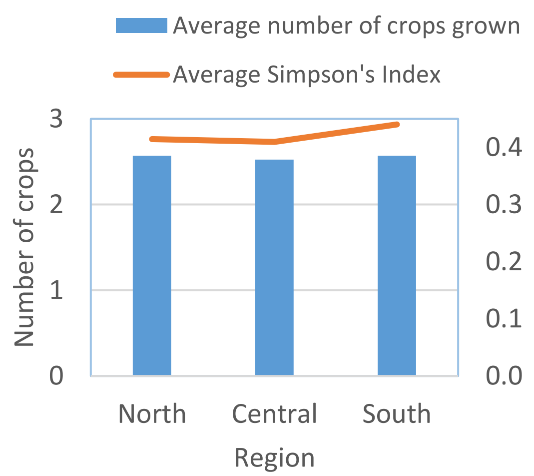
(b) Average number of crops grown and SDI over time



(c) Number of crops grown by region (2004–2016)



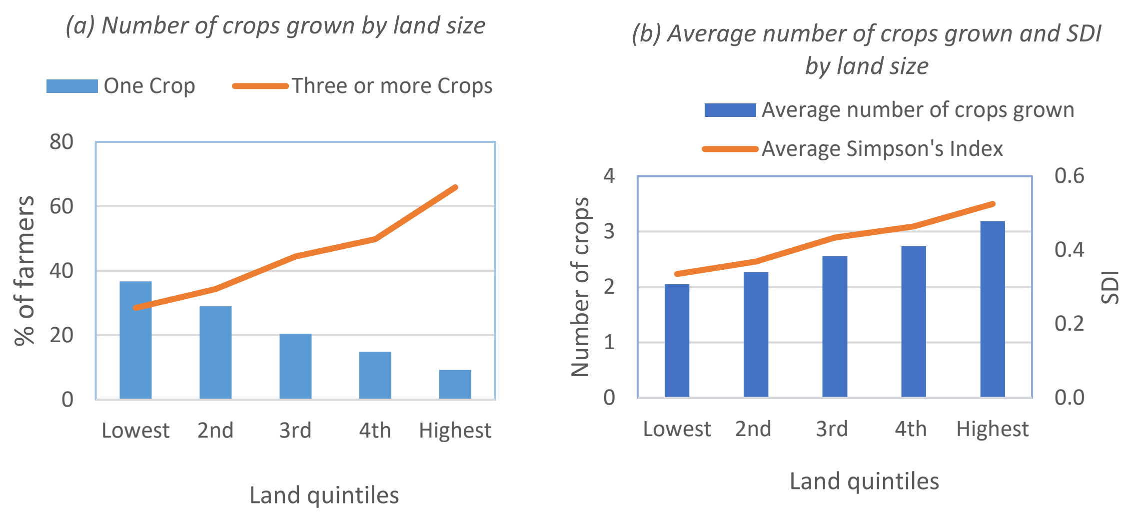
(d) Average number of crops grown and SDI by region (2004–2016)



Source: Authors' calculation based on IHS 2–4.

The lack of cultivable land appears to be the main reason why smallholder farmers rely heavily on maize as their sole crop. The level of crop diversification is much lower among farmers with limited land, that is, those in the lowest landholding quintiles (Figure 3-2a). These farmers typically grow maize only for own consumption. Whereas, in the highest landholding quintile, only a small fraction of farmers grows just maize. In fact, about two-thirds of these farmers grow three or more crops. The average number of crops grown increased steadily over the size of landholding. Households in the lowest landholding quintile grow on average only two crops compared to more than three crops for those in the highest quintile. Similarly, the SDI increases with landholding (Figure 3-2b).

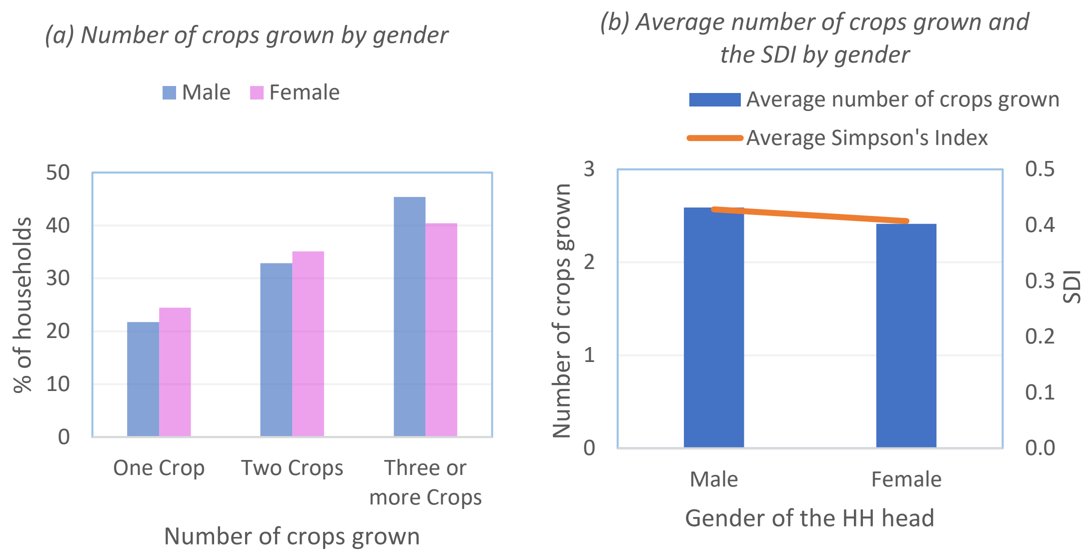
Figure 3-2: Farmers with larger landholding are more likely to diversify, while land-constrained households specialize in one crop, typically maize



Source: Authors' calculation based on IHS 2–4.

Like the differences by region, households that grow three or more crops are the largest group for both male- and female-headed households. The proportion of male-headed households that grow three or more crops are slightly higher than their female counterparts (Figure 3-3a). Both the average number of crops grown and the SDI are quite similar between the two groups (Figure 3-3b).

Figure 3- 3: Crop diversification is similar for male-headed and female-headed households

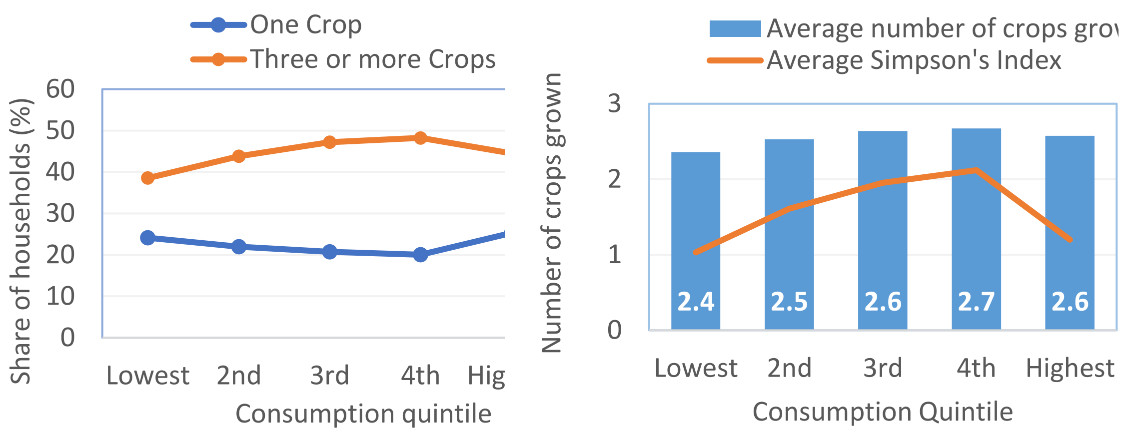


Source: Authors' calculation based on IHS 2–4.

Crop diversification appears to be associated with higher level of consumption per capita. However, the richest farmers appear to specialize in fewer crops. The proportion of households that grow three or more crops increases steadily with the consumption quintile before it slightly decreases for the top quintile. Similarly, the proportion of households that grow just one crop slowly decreases as the consumption level increases, with the richest households tending to specialize more in one crop (Figure 3-4a). The average SDI figures also show more crop specialization occurring among households in the bottom and top consumption quintiles compared to those in the middle quintiles (Figure 3-4b). For wealthier farmers with better capacity to mitigate risk from failure of a single crop, specializing in one crop could be advantageous as they could increase productivity in that crop. While, poor farmers with smaller landholdings specialize in one crop (typically maize) to satisfy food demand at the household level. This could be the reason we observe (inverted) U-shape patterns in Figures 3-4a and 3-4b.

Figure 3-4: Diversification is associated with higher consumption. However, farmers in the highest consumption quintile specialize in fewer crops

(a) Number of crops grown by consumption quintile *(b) Average number of crops grown and the SDI by consumption quintile*

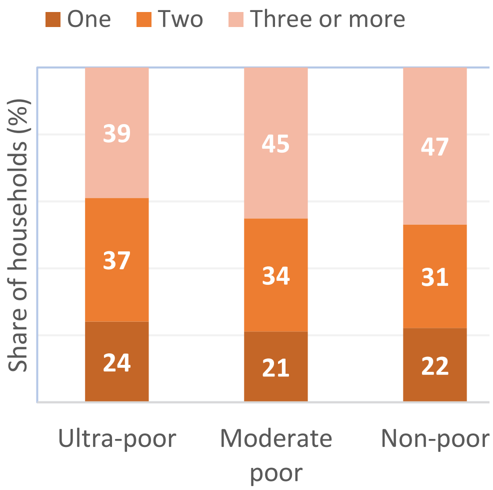


Source: Authors' calculation based on IHS 2–4.

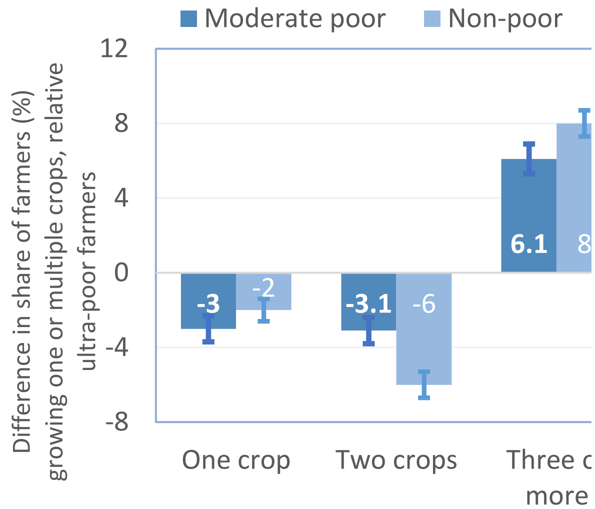
Ultra-poor households tend to specialize in one or two crops compared to moderate poor or non-poor households. The association of diversification with poverty is presented in Figures 3-5a to 3-5d. About 47 percent of the non-poor households grow three or more crops, followed by 45 percent of moderate poor households. However, on each acre of cultivated land, non-poor households are less diversified than poor households. This suggests that the scope for crop diversification may be limited even for non-poor households with relatively larger landholdings.

Figure 3-5: Crop diversification is positively associated with escaping poverty. However, ultra-poor households have more crops per acre of cultivated land

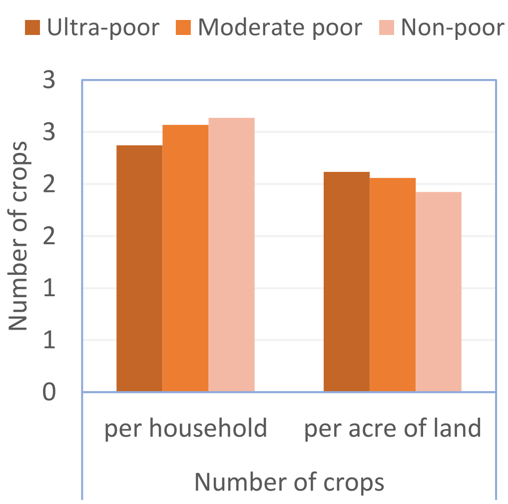
(a) Share of poor and non-poor farmers growing one versus multiple crops



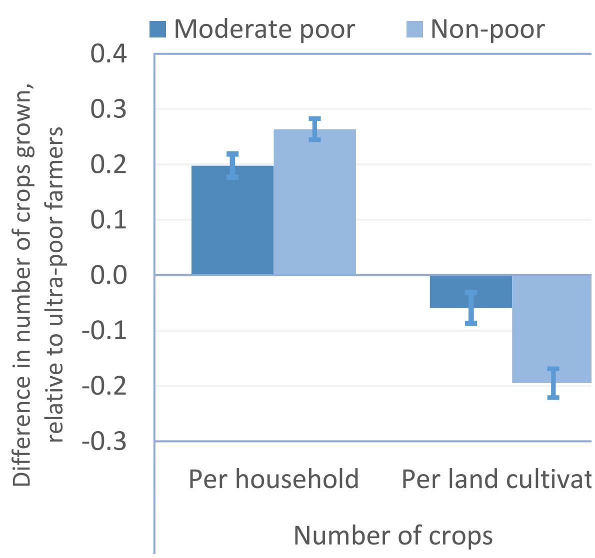
(b) Difference in diversification levels of moderate poor and non-poor, relative to ultra-poor farmers



(c) Number of crops grown by poverty status



(d) Difference in number of crops grown by moderate poor and non-poor, relative to ultra-poor farmers



Source: Authors' calculation based on IHS 2–4.

To understand the types of households that are able to diversify, the report compares characteristics of monocrop farmers with diversified farmers (Table 3-2). The results show that diversified households are more likely to have elderly members and to be headed by an educated male than single crop farming households. There are no discernible differences on the likelihood of the head engaging in nonfarm enterprises or being employed for wages.

Farmers who own larger areas of cultivable land and multiple plots are more likely to diversify. These diversified farmers are also more likely to use fertilizer on their crops and apply fertilizer more intensely, compared to undiversified farmers. In addition to landholdings and technology adoption those that have experienced crop shocks such as droughts and crop diseases are more likely to diversify. Their exposure to shocks may, indeed, partly explain why they opted to diversify their crop portfolios.

Table 3-2: Average socioeconomic characteristics of monocrop and diversified farmers (2016/17)

Variables	Monocrop farmers	Diversified farmers	Difference
Household size	5.2	5.3	0.07
Number of children	2.59	2.58	−0.01
Number of elders	0.13	0.16	0.03***
Number of working-age members	2.50	2.54	0.05
Dependence ratio	1.36	1.35	−0.01
Household head characteristics			
Female	0.28	0.26	−0.02*
Literate	0.79	0.83	0.04***
Years of education	5.18	5.34	0.16*
Work in nonfarm enterprise	0.12	0.11	−0.01
Work for wage	0.10	0.11	−0.01
Area of cultivated land	1.2	1.7	0.44***
Number of plots	1.2	3.3	2.07***
Shocks to crop	0.56	0.70	0.13***
Applied fertilizer (on any plot)	0.5	0.7	0.15***
Fertilizer intensity (kg/ha)	30.8	35.2	4.37***
Number of observations	2,096	7,359	

Source: Authors' calculation based on IHS 4.

Note: *, **, and *** show the difference in means is significant at 10 percent, 5 percent, and 1 percent significance levels respectively. Diversified farmers grow two or more crops on their fields.

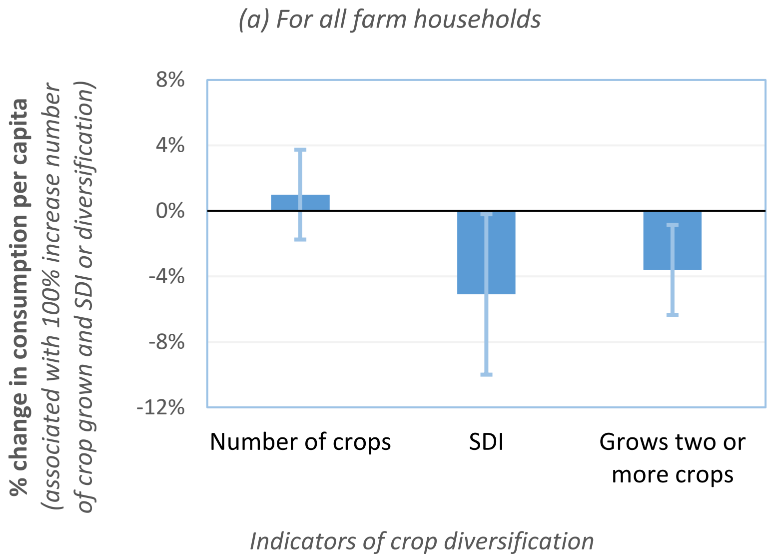
3.4. Empirical Results

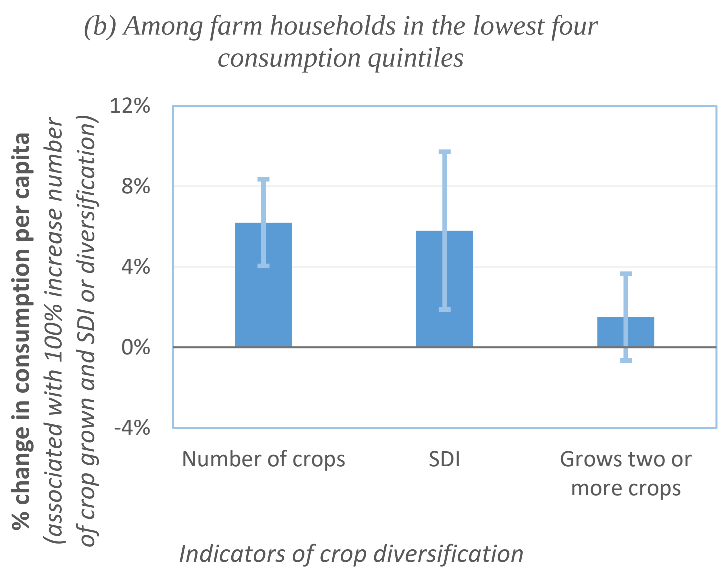
A detailed analysis of association between crop diversification and welfare indicates that, in the overall population, diversification is weakly associated with consumption per capita. This section presents results from a regression analysis of the links between crop diversification and consumption levels as well as poverty after accounting for other socioeconomic factors such as household characteristics, use of agricultural technology, and district and year FEs. Figure 3-6a shows results from an OLS regression of (log) consumption per capita on indicators of diversification—that is, (log) number of crops and (log) the SDI as well as a dummy equal to one if the household grows two or more crops—using data on all farm households. The association between two of the three diversification indicators and consumption per capita is not significant when all households are considered, while consumption per capita is lower for households that grow two or more crops. This unexpected result may be due to the findings (see Figure 3-4) that crop diversification increases by consumption quintiles till the richest quintile wherein households tend to specialize in selected crops. Therefore, we investigate the association between consumption and diversification for households in the lower four consumption quintiles (Figure 3-6b).

Diversification is positively associated with welfare improvement for those households in the lower four consumption quintiles. Figure 3-6b shows association between consumption and diversification among households in the lowest four consumption quintiles. Farm households that are able to increase the number of crops grown, for example, from two crops to four crops (by 100 percent increase) tend to have 6 percent higher real consumption per capita. Similarly, a 100 percent increase in the SDI is associated with a 6 percent higher consumption per capita. However, comparing households that grow just one crop with households that grow two or more crops did not yield significant differences in consumption levels after controlling for other factors.

Figure 3-6: Diversification is positively associated with welfare for households in the lower four consumption quintiles

Association between consumption and crop diversification





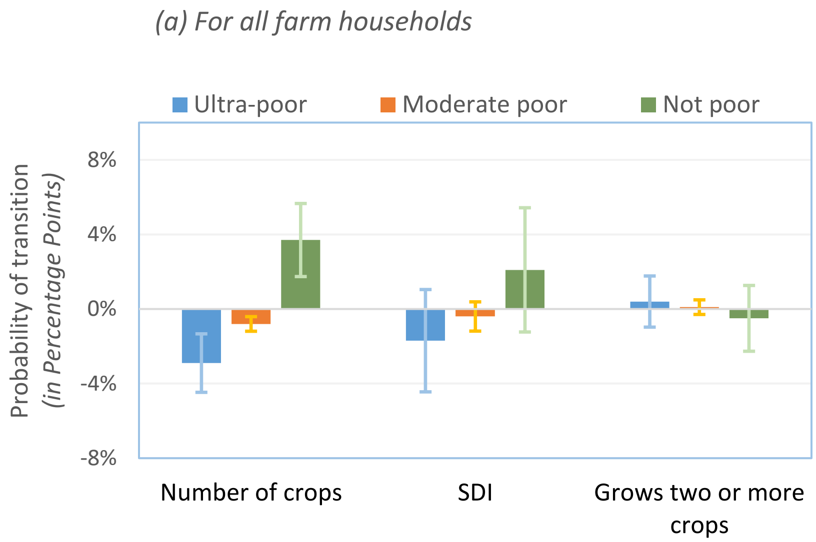
Source: Authors' calculation based on IHS 2–4.
Note: The results are from one of six OLS regression estimations with (log) consumption per capita as the dependent variable, and the three indicators of diversification (and other controls) as independent variables. The control variables include key household characteristics, and year and district FEs. The error bars show the 95 percent confidence interval. The full regression estimates are reported in Tables A1 and A2 in the Appendix.

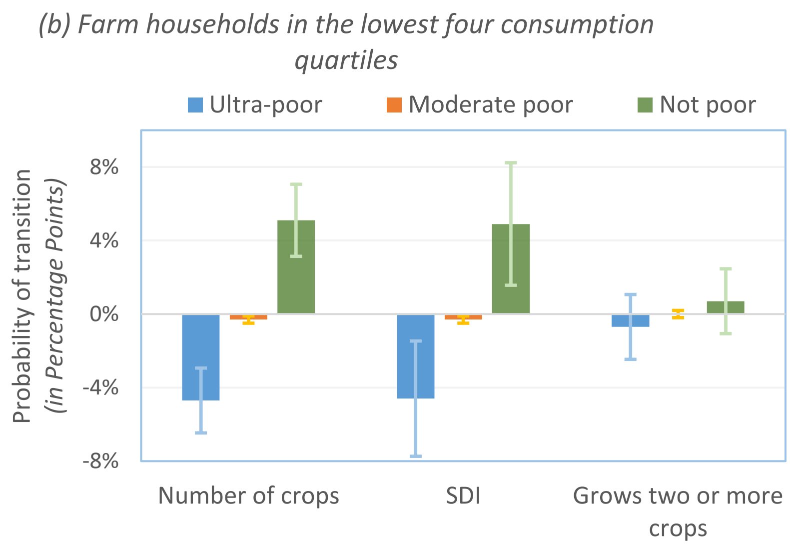
Households that grow more crops or have higher SDI are less likely to remain ultra-poor. To study the association between poverty and crop diversification, we use an ordered logit regression of poverty status (ultra-poor, moderate poor, or non-poor) on measures of crop diversification (and other control variables). The results from this analysis are presented in Figure 3-7a (all farm households) and Figure 3-7b (farm households in the lowest four consumption quintiles). The results show a negative correlation between our two measures of diversification—(log) the number of crops grown and (log) the SDI —and ultra-poverty. For example, increasing the number of crops grown by 100 percent, say from two crops to four crops, is associated with 5 percentage points lower probability of being ultra-poor (Figures 3-7). Similar results hold for the SDI.

Conversely, growing more crops is positively correlated with escaping poverty. A 100 percent increase in the number of crops grown or the SDI is associated with 5 percentage points higher probability of being non-poor. This finding is not surprising given that the poverty measures were directly calculated from the total consumption expenditures. We found a similar relationship between consumption and number of crops grown as well as the SDI.

The relationship between poverty levels and whether the household grows two or more crops is largely inconclusive. This is true regardless of whether we consider the full sample or exclude households in the top consumption quintile (Figures 3-7). Again, this finding is similar to the relationship between consumption levels and this indicator variable discussed earlier.

Figure 3- 7:Association of crop diversification with transition out of poverty ***(Percentage point changes in the likelihood of households being in each poverty status after a 100 percent change in the number of crops grown/SDI or after becoming diversified)***



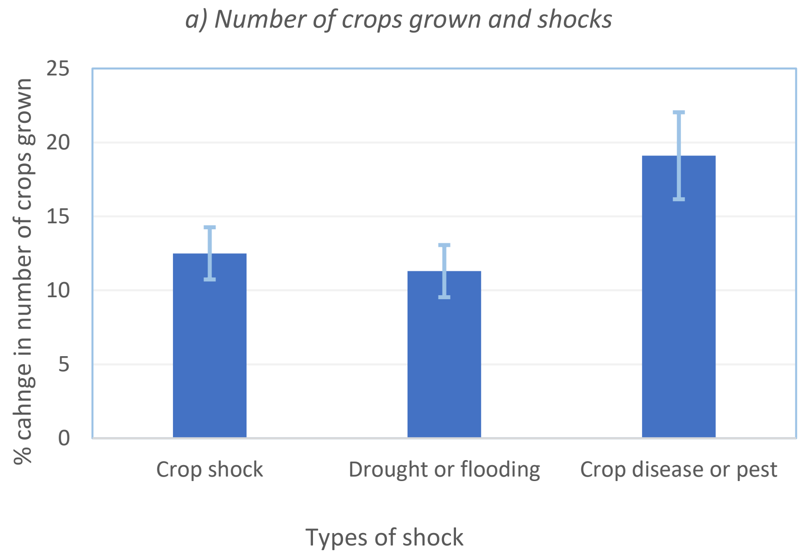


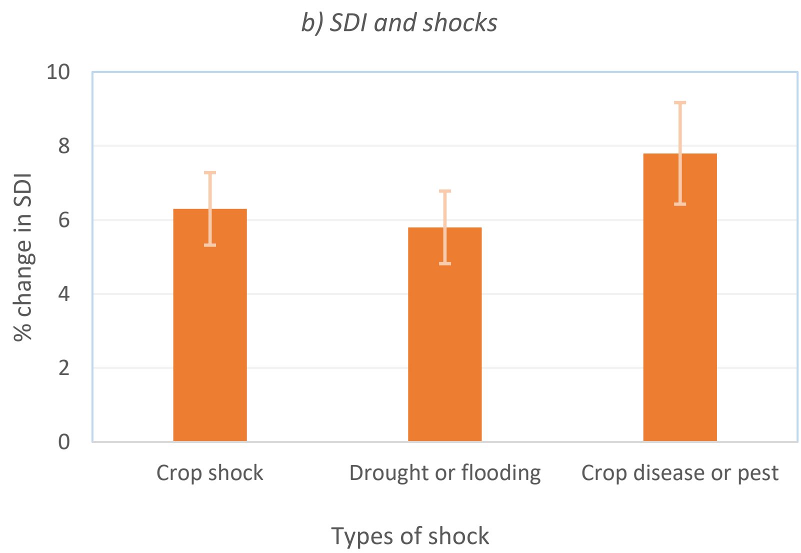
Source: Authors' calculation based on IHS 2–4**.**
Note: These results are the marginal effects from the ordered logit model for transition from ultra-poor to moderate poor, and from moderate poor to non-poor. The error bars show the 95% confidence interval. The standard errors are robust and clustered at the enumeration area level. The full regression estimates are reported in Tables A3 and A4 in the Appendix.

Households that were exposed to crop shocks are more likely to diversify their crop portfolios than those that did not experience shocks. Results from an OLS regression analysis of crop diversification measures on households' exposure to different types of crop shocks such as drought/flooding and crop disease/pest are presented in Figures 3-8a and 3-8b. Households that have experienced crop disease or pest grow 20 percent more crops on their farms compared to households that did not experience these shocks. The SDI is also higher by 8 percent for households that have experienced crop disease or pest compared to households that did not experience this shock. While these estimates are not causal, they suggest that farmers may engage in crop diversification to mitigate the consumption shocks that result from their previous exposure to droughts, flooding, or crop diseases.

Figure 3- 8: Households that are affected by shocks in previous season are more likely to diversity their crop portfolios

Correlation between the decision to diversify and exposure to shocks





Source: Authors' calculation based on IHS 2–4.
Note: These results are from an OLS regression of diversification indicators on shocks in the previous season, household characteristics, as well as district and year FEs. The error bars show the 95 percent confidence interval. The full regression estimates are reported in Tables A5 and A6 in the Appendix.

3.5. Conclusion and Policy Implication

The evidences presented in this study suggest that diversified households enjoy better consumption, are more likely to be non-poor, and have had previous experience of shocks to their crop production.

Households that engage in crop diversification also tend to have higher consumption levels and because of this positive relationship, crop diversification is also positively correlated with escaping poverty. These positive relationships are stronger for households in the bottom four consumption quintiles.

In addition, households that have experienced crop shocks are more likely to engage in crop diversification on their farms than households who did not experience any such shocks. These results suggest that farmers may engage in crop diversification to mitigate the consumption shocks that result from their previous exposure to droughts, flooding, or crop diseases.

Our findings suggest that policymakers should incorporate crop diversification in Malawi's poverty reduction program and support farmers in their diversification effort. However, our results also suggest that relatively rich farm households may still benefit from specialization of crop production to take advantage of the scale effects from larger land sizes. Thus, the promotion of crop diversification should be targeted towards relatively poor households that are most vulnerable to crop shocks.

Some of the measures that could promote diversification include addressing lack of market information and high market risk, introducing crop insurance, providing information on crop diversification through extension programs, facilitating the use of agricultural technologies, and supporting agricultural R&D. The existing agricultural extension system can be leveraged to disseminate essential information and advice to farmers about the benefits of crop diversification and foster the adoption of best agronomic practices such as intercropping in maize dominant farming systems.

4. Does Inclusion of Large Farms Reverse the Inverse Farm-Size Productivity Relationship? Evidence from Ethiopia

Daniel Ali[**], Klaus Deininger[++], and Sinafikeh Gemessa

4.1. Introduction

A common feature in the literature on agricultural production in developing countries has been the existence of an inverse farm-size and productivity relationship. In fact, the vast majority of studies on this topic start their papers by acknowledging this (see, for example, Bevis and Barrett 2016; Kagin et al. 2016; Ali and Deininger 2014; Carletto et al. 2013; Barrett 1996; and Benjamin 1995 to cite just a few). These observations are puzzling because under the common assumption of constant returns to scale and perfect competition, land productivity should be equal across production units (Kagin et al. 2016). Thus, in this case, the neoclassical theory of equal marginal productivity between production units would not hold at equilibrium (Bevis and Barrett 2016). These results also have policy implications. More specifically, if the inverse farm-size and productivity relationship is properly identified, then a land redistributive policy of breaking up larger farms to smaller plots could be justified on efficiency grounds.

Researchers have put forward many other potential explanations for this relationship, however. The most common explanations include application of more than the optimum amounts of agricultural inputs due to imperfections in labor, land, and insurance markets (for example, Sen 1972; Feder 1985; Barrett 1996).

Measurement error in land size may also result in spurious inverse relationship between land size and productivity (see, for example, Lamb 2003; carletto et al. 2013). Systematic measurement error in output could also influence the IR relationship. Desiere and Jolliffe (2018) investigate the IR using yield values calculated from self-reported and crop-cut output. Crop cut measures are considered the gold standard in output measurement. Their main finding is that when crop cuts are used to measure yields, the plot-size IR disappears. In contrast, when they use self-reported yield, the relationship is strongly negative suggesting that production is systematically over-reported on

[**] Senior Economist, World Bank, dali1@worldbank.org
[++] Lead Economist, World Bank, kdeininger@worldbank.org

small plots and under-reported on larger ones. Gourlay et al. (2017) found similar results among maize farmers in Uganda. Abay et al. (2019) contend that such types of measurement error may reflect not only misreporting by respondents but also misperceptions arising from mistaken beliefs they hold about their land size or output and on which they act. In such cases, a simple correction of measurement errors using objective measurement methods may not accurately explain behavioral parameters of interest. Of course, distinguishing misreporting from misperceptions in survey data is often very difficult to achieve.

Omitted variable bias related to unobserved soil quality differences between large and small farms could also explain the inverse relationship (see, for example, Benjamin 1995 and Barrett et al. 2010). In addition to the above potential explanations, an interesting behavioral dimension has also been put forward recently by Bevis and Barrett (2016). The authors explained the inverse relationship between productivity and cultivated area in Uganda as a result of “edge effects”. This occurs when farmers work harder along the edges than they do in the middle of their plots as they can observe and get better access to the edges. Thus, small plots that tend to have larger perimeter to area ratio than bigger plots get more intensive labor inputs. Biophysical effects, such as different levels of nutrients around the edges and better exposure to sunlight was also not ruled out by the authors.

Most empirical investigations into the oft-observed inverse relationship between farm size and productivity use data from smallholder agriculture. Table 4- below summarizes the mean and standard deviation of cultivated area as reported by various studies. While the list in Table is not exhaustive of papers written on this issue, the average farm sizes are representative of what researchers have mainly focused on. The Table shows that the average cultivated area ranges from just 0.46 hectares (ha) in Rwanda (Ali and Deininger 2015) to 9.92 ha in Nicaragua (Henderson 2015) with the median reported average farm-size at just 2.24 ha.

Table 4- 1: Mean and Standard Deviation of Cultivated Area in Hectares (ha) Studied in Various Papers

Paper	Country	Mean	S.D.
Muyanga and Jayne (2019)	Kenya	13.39	-
Bevis and Barrett (2016)+	Uganda	0.82	0.88
Kagin et al. (2016)	Mexico	1.5 (small farms) & 9.89 (large farms)	-
Ali and Deininger (2015)	Rwanda	0.46	-
Henderson (2015)	Nicaragua	9.92	18.21
Carletto et al. (2011)	Uganda	2.24	12.47
Chen *et al.* (2011)	China	0.66	0.59
Barrett *et al.* (2010)	Madagascar	6.64	7.70
Lamb (2003)	India	0.88	-
Heltberg (1998)	Pakistan	3.00	-
Benjamin (1995)	Indonesia	0.76	0.01
Carter (1984)	India	3.02 (small farms) and 8.46 (large farms)	0.713 (small farms) and 5.03 (large farms)
Median	-	2.24	

Note: + Reported value is median not mean. Units are hectares. The S.D. values are not reported for many papers.
Source: Various papers.

Muyanga and Jayne (2019) & Foster and Rosenzweig (2017) recognized the overwhelming focus on smallholder farmers to investigate the farm size- productivity relationship and included medium-scale farmers in their samples. Muyanga and Jayne (2019) use three different measures of productivity including gross and net value of output per hectare and total factor productivity to test the inverse relationship hypothesis for Kenya’s high-potential zones between zero and 70 hectares. They report a U-shaped relationship between farm size and all three measures of farm productivity. This relationship is maintained in Foster and Rosenzweig (2017) for India. The authors consider farmers with size of landholdings up to 12 hectares. They show that labor-market transaction costs can explain why the smallest farms are most efficient, slightly larger farms are least efficient and larger farms are as efficient as the smallest farms.

This paper aims to contribute to the literature by including both medium- and large-scale commercial farms in the empirical analysis of the inverse relationship between farm size and productivity. To do this, we use data that come from the last two rounds of Ethiopia’s Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) that were collected in 2013/14 and 2015/16 and the Central Statistical Agency's (CSA) Large and Medium Scale Commercial Farms Survey collected in 2014/15 and 2015/16.

The mean farm size among small, medium, and large-scale farm operators in our sample are 1.2 ha, 29.5 ha, and 427.9 ha respectively. This represents a much wider range of farm sizes than previously considered by other studies.

Inclusion of commercial farms in the analysis of the inverse relationship between farm size and productivity has also direct policy relevance. This is because since about 2008, large commercial farms have received substantial attention by both policymakers and investors alike. During this time, investments in large-scale farming rose rapidly in land abundant developing and transitioning countries (Deininger and Byerlee 2012).

Collier and Dercon (2014) argue that large commercial farms are important for experimenting and pushing the technological frontier in African agriculture. Collier and Venables (2012) further maintain that due to the increasing importance of technological innovation, finance, fast and reliable logistics, and marketing connections large commercial farms do better than smallholder farmers. However, compared to smallholder farming, commercial farms are also more likely to suffer from moral hazard problems such as shirking as they rely heavily on hired labor. It is, therefore, important to understand if commercial farms are able to overcome the inverse relationship between farm size and productivity that has been documented widely for small-scale agriculture.

For the econometric analysis, we employ year and village fixed effects linear regression method. This will help control for time-invariant unobserved heterogeneity at the village level. For robustness checks, we control for district-level fixed effects. We measure yield as quintals of output per hectare. We consider the five major grain crops grown in Ethiopia namely maize, sorghum, teff, wheat, and sesame. These are among the most commonly grown crops in Ethiopia. In the 2017/18 planting season alone, the first four crops constitute about 86% and 87% of all cereal acreage and quantity of production in the country respectively (Government of Ethiopia, 2018). This is, indeed, another contribution of the paper as it presents the econometric results for each crop and compares them with each other. This helps to understand if the inverse relationship (IR) between farm size and productivity is limited to specific crops or exists across the major crops in the country.

Our findings confirm the empirical regularity of the IR between farm-size and productivity for small-scale agriculture that has been well documented in the literature. This is true for each of the crops considered in this study. The results for medium- and large-scale farms are mixed. For medium-scale farms, we found no relationship between crop area and productivity for all the crops except Teff, in which case the IR is observed. For large-scale farms, the IR is maintained for all the crops except maize. These results are largely robust to the inclusion or exclusion of other inputs as controls and whether we use village or district fixed effects.

This paper is organized as follows. The next section presents the econometric approach adopted. Section 4.3 describes the data and the variables used. Section 4.4 presents the empirical results while section 4.5 discusses the results from the robustness checks. The last section concludes the paper.

4.2. The Econometric Approach

To examine the relationship between productivity and farm-size at farm holding level, we estimate the following aggregate yield equation, which is similar to those estimated by Ali and Deininger (2015), Assuncao and Braido (2007), and Barrett et al. (2010), among others.

The specification takes the form:

$$Y_{it} = \alpha A_{it} + \gamma' X_{it} + \theta_j + \delta_t + \varepsilon_{it}\ , \qquad (1)$$

where Y_{ijt} is the (log) of yield or productivity for farm holding i in year t. Yield is measured in quintals of output per hectare (for specific crops). The variable A_{it} is (log) size of cultivated area by farm holding i in year t. All area measures are collected using handheld Global Positioning System (GPS) devices. The coefficient α allows us to test the inverse relationship (IR) between yield and size of cultivated area. The vector X_{it} includes farm characteristics that capture the use of different inputs and experience with crop shocks. The variables θ_j and δ_t are village and year fixed effects respectively. For robustness checks, we replace the village with district fixed effects. Finally, ε_{it} is an error term that captures, for example, measurement errors in the dependent variable.

To estimate equation (1), we employ village (or district) fixed effects linear regression method. This method helps control for unobserved village or district level heterogeneity that is fixed over time. The choice of explanatory variables in the vector X_{ijt} is guided by theory, literature, and available data.

One important source of bias in estimating α identified in the literature is measurement error in the farm size variable. This results in attenuation bias (Lamb 2003). This paper largely avoids this problem as the data on cultivated areas is collected using GPS devices. While this method is not perfect, it is considered much better than farmers' estimation. We assume that any remaining error in GPS measured area is unrelated to the farm size. We also recognize that other sources of bias such as the quality of land or unobserved heterogeneity at the farm level such as the managerial ability of the household head could, potentially, bias our estimates. We argue that to some extent, quality of land is imperfectly controlled for by our village-level fixed effects as a typical village covers relatively small area comprised of around 400 households on average.

Use of agricultural inputs such as improved seeds and chemicals such as chemical fertilizer, herbicides and fungicides are also controlled for as they may be correlated with farm size. A dummy variable for crop shocks is also included. This captures incidence of any environmental shocks that affect crop output such as droughts, floods, and diseases experienced by the household/enterprise and is often overlooked in the literature despite being clearly correlated with crop area allocation decisions.

4.3. Data and Descriptive Statistics

The data used in this paper come from the last two rounds of Ethiopia's Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) that were collected in 2013/14 and 2015/16 and the Central Statistical Agency's (CSA) Large and Medium Scale Commercial Farms Survey (henceforth referred as 'commercial survey') that were collected in 2013/14 and 2014/15. While the LSMS-ISA data are panel in nature and follow small scale farms (those with less than 10 ha of land under operation) over time, the commercial survey employs a repeated random sampling of medium scale farms (between 10 ha and 50 ha) while following the same large farms (over 50 ha) over time. Both the LSMS-ISA and the commercial survey data are representative at the national level and at regional level for the country's major regions (Central Statistical Agency and World Bank 2017; Central Statistical Agency 2015).

The commercial survey collects basic quantitative information on crop land area and production for both temporary and permanent crops. Information on modern farm inputs such as tractor, improved seed, chemical fertilizer, and pesticides are collected. Data on farm labor use are also collected under this survey. The LSMS-ISA data is much more detailed compared to the commercial survey and includes information about households' socio-economic characteristics, agricultural and non-agricultural activities, consumption, assets, among others. Both surveys employ handheld GPS assisted measurement of cultivated areas.

In this paper, we focus on the five major crops grown in the country namely maize, wheat, teff, sorghum, and sesame. In the 2017/18 planting season alone, the first four crops constitute about 86% and 87% of all cereal acreage and quantity of production in the country respectively (Government of Ethiopia, 2018). Sesame is also a major oilseed crop grown mainly for export. In 2017/18, the crop accounted for 44% and 30% of oilseed acreage and production amount respectively (Ibid).

Table 4-2 below shows the number of operational farms in the sample, average cultivated area, and distribution of crop choice by farm size categories. The Table shows that when we combine the LSMS-ISA dataset with the commercial survey, smallholder farmers dominate the sample distribution. This is unsurprising given the structure of Ethiopia's agricultural economy, where most farming occurs by smallholder farmers. On average, small-scale farms operate about 1.2 ha of land compared to about 30 ha for medium farms and 428 ha for large farms. Of the major grain crops grown in Ethiopia, maize, teff, and sorghum are among the most commonly grown crops by small-scale farmers. By contrast, Sesame takes up by far the largest share of crop area among medium and large-scale farms. The prevalence of sorghum and maize crops follow at distant second and third places respectively among these farms.

Table 4-2: Crop choice by farm size

	Small (<10 ha)	Medium (10 - 50 ha)	Large (> 50 ha)
Number of operational farms	4877	1287	3162
Total cultivated area (all crops) in ha	1.22	29.46	427.87
Share of maize	18.34	9.55	9.53
Share of wheat	9.69	2.28	5.52
Share of teff	15.91	4.17	1.01
Share of sorghum	13.56	25.59	19.39
Share of sesame	2.06	47.20	49.82
Share of other grains	40.44	11.21	14.74

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.

Average farm level characteristics including input use and yield are presented in Table 4-3 by category of farm size. The descriptive statistics results show that, on average, smallholder farmers allocate 0.87 ha to the main crops described above compared to 27.13 ha and 328.25 ha for medium and large-scale farms respectively. About half of small- and medium-scale farms use chemical fertilizer on their fields. Around two-thirds of large farms use chemical fertilizer in their farm production but with lesser intensity (i.e., Quintal/ha) than their small and medium farm counterparts. Improved seeds are much less prevalent with less than a quarter of farms adopting this technology regardless of farm size. Applications of herbicides are more common than either pesticides or fungicides. There is very low adoption of irrigation across the three farm-size categories with medium-scale farms employing it more often than both small and large farms. Surprisingly, most medium and large-scale farm enterprises reported experience with crop shocks such as droughts, flooding, and crop diseases. By contrast, less than half (41%) of smallholder farmers experienced crop shocks.

Table 4-3 also shows that, as expected, large-scale farms are more likely to own machineries like tractors, water pumps, harrower, and combine harvester compared to medium or small-scale farms. The average yield amounts are comparable for medium and large-scale farms and they are significantly higher than small-scale farms. This is especially true for maize and wheat, where the amount of output per ha for medium and large-scale farms are close to double the corresponding value for small-scale farms.

Table 4-3: Farm level descriptive statistics

	Small (<10 ha)	Medium (10 - 50 ha)	Large (> 50 ha)
Input use			
Cultivated area of main crops in ha	0.87	27.13	328.25
Used chemical fertilizer	0.50	0.45	0.68
Chemical fertilizer used (Quintal/ha)	1.52	1.02	0.84
Used improved seeds	0.14	0.21	0.22
Used pesticides	0.04	0.12	0.21
Used herbicides	0.21	0.26	0.34
Used fungicides	0.02	0.02	0.06
Used irrigation	0.02	0.13	0.07
Affected by crop shock	0.41	0.80	0.87
Has own tractor	0.01	0.44	0.77
Number of tractors owned		1.51	1.88
Has water pump		0.18	0.30
Has machine pulled plow/harrower		0.38	0.57
Has combine harvester		0.06	0.16
Yield			
Maize (quintals/ha)	22.95	37.39	38.27
Wheat (quintals/ha)	14.92	29.74	21.62
Teff (quintals/ha)	8.27	13.77	14.45
Sorghum (quintals/ha)	14.67	25.07	24.55
Sesame (quintals/ha)	5.34	8.92	7.43
Number of observations (farms)	4489	1481	2881

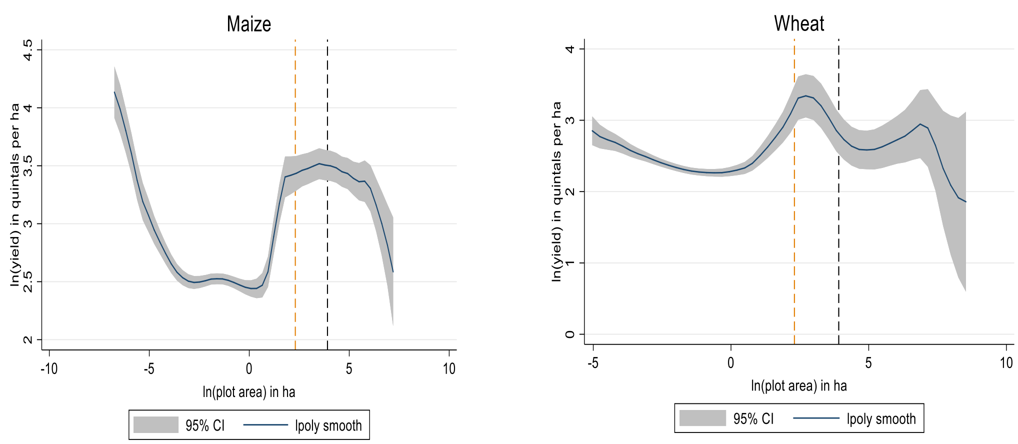
Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey. Restricted to plots under maize, wheat, teff, sorghum and sesame.

In addition to the average characteristics presented in Table 4-3, we also investigate the direct relationship between yield and size of cultivated area using non-parametric methods. The smoothed local polynomial regression results are presented in Figure 4-1 for each of the major crops considered in this study. For each grain crop, there is largely a U-shaped relationship between quintals of production per ha and crop area up to 10 ha of land or small-scale farms. For medium-scale farms, yield decreases with increasing crop area for wheat, sorghum, and sesame crops. The opposite seems true for Teff crop and maize yield levels off for these farms.

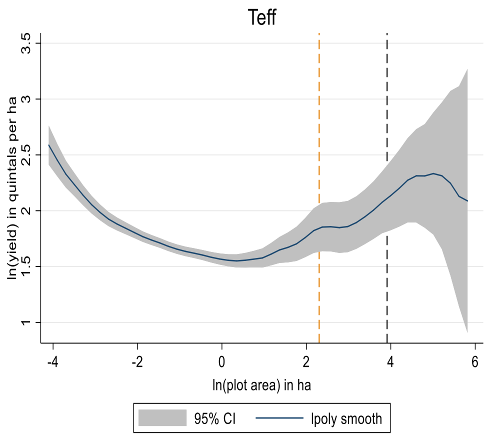
For large-scale farms, which operate more than 50 ha of land, yield decreases substantially for maize and sorghum crops with increasing crop area. For wheat and sesame crops, yield decreases more slowly with increasing area among these farms. There is a lot of uncertainty around Teff yield for large-scale farms. This stems from the fact that very few commercial farms plant the crop as the government put restrictions on exporting unprocessed teff grain (Minten and Taffesse, 2018). The government has cited the potential adverse impacts on local teff consumption resulting from increased domestic prices of the grain as teff marketing becomes liberalized.

Figure 4- 1: Kernel-Weighted Local Polynomial Regression of Crop Yield (log) on Crop Area (log)

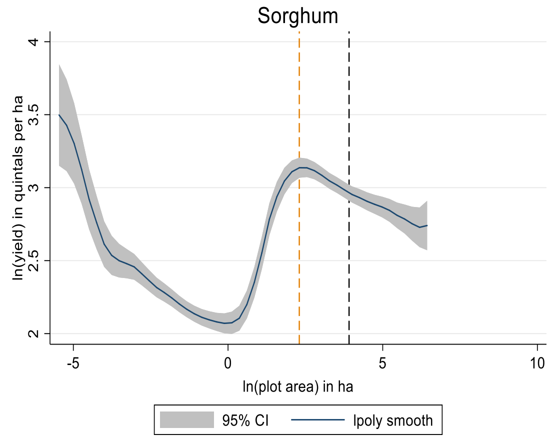
Panel (A) **Panel (B)**



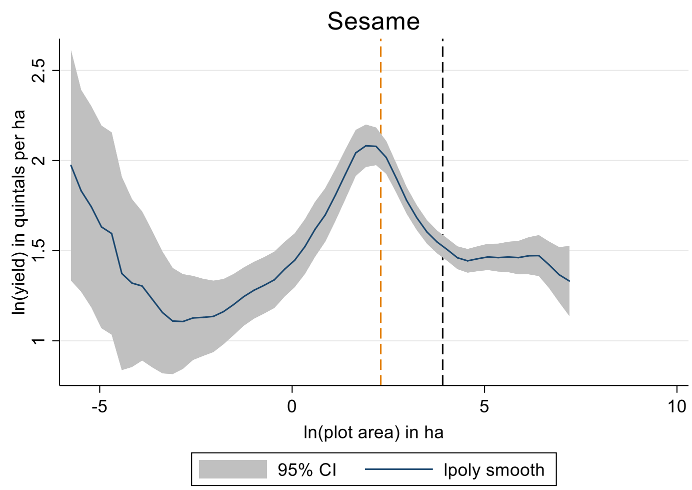
Panel (C)



Panel (D)



Panel (E)



Note: The first and second dotted lines are markers for 10 ha and 50 ha of land respectively.
Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.

4.3. Empirical Results

To investigate the relationship between productivity and farm size, we estimate village and year fixed effects linear regression of yield on farm size and other covariates. As shown in Table 4- 3, yield is measured in quintals of output per hectare (ha) for each of the five major grain crops grown in the country. We have log transformed the dependent variable and farm size measures so that the key coefficients of interest are expressed in elasticity. For each of the major crops, the econometric results are presented separately for small-scale (less than 10 ha), medium-scale (between 10 and 50 ha), and large-scale (above 50 ha) farms. The estimation for smallholder farmers is comparable to most previous studies that focus on these subjects.

The regression results presented in Table 4 for smallholder farmers show that for maize crop, there is significant and inverse relationship between crop area and yield regardless of the specification considered. In fact, when we control for some potential explanations for the IR such as use of different chemical inputs, access to labor, and experience with crop shocks, the IR endures and becomes even stronger (see m1 and m2 in Table 4-4).

The regression results for medium and large-scale farms suggest that there is no significant relationship (positive or negative) between maize yield and crop year (Table 4-4). For medium farms, this result seems to go in-line with the results from the non-parametric regressions discussed in Figure 4-1A. For large-scale farms, the negative non-parametric relationship between maize yield and farm size that we observe in Figure 4-1A seems vanish when we control for very important inputs such as amount of chemical fertilizer and improved seeds per hectare. Thus, for a given level of input use, large-scale farms seem to be equally efficient in their production of maize crops per unit of land.

Table 4-4: IR estimates for maize yield per ha: village fixed effects

	Small (<10 ha)		**Medium (10 - 50 ha)**		**Large (>50 ha)**	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.154***	0.154***	-0.563	-0.631*	-0.029	-0.058
	(0.027)	(0.027)	(0.384)	(0.346)	(0.074)	(0.073)
Ln(crop area in ha)	-0.408***	-0.412***	0.145	0.220	-0.120	-0.109
	(0.022)	(0.023)	(0.117)	(0.154)	(0.088)	(0.088)
Arcsinh(chemical fertilizer use in quintals per ha)	0.255***	0.224***	2.468***	1.596***	27.173**	21.634*
	(0.039)	(0.040)	(0.208)	(0.453)	(12.321)	(12.052)
Arcsinh(No. of workers per ha)	0.173***	0.175***	0.212	0.086	0.004	-0.001
	(0.031)	(0.031)	(0.134)	(0.164)	(0.060)	(0.065)
Used pesticides		-0.089		0.552		0.177
		(0.131)		(0.491)		(0.167)
Used fungicides		-0.388*		-		-0.033
		(0.229)				(0.123)
Used herbicides		0.157		1.605*		0.024
		(0.096)		(0.952)		(0.120)
Used improved seeds		0.152**		-0.185		0.343*
		(0.066)		(0.578)		(0.205)

Experienced crop shocks		-0.273***		-0.502		-0.301**
		(0.046)		(0.370)		(0.129)
Year=2014[a]	0.063	0.014	0.340	-0.057	-0.314	-0.218
	(0.059)	(0.057)	(0.471)	(0.528)	(0.242)	(0.237)
Constant	1.080***	1.189***	4.178***	4.940***	3.936***	3.949***
	(0.099)	(0.100)	(1.149)	(1.327)	(0.489)	(0.399)
Number of observations	2,961	2,961	119	118	414	404
R2	0.224	0.246	0.335	0.430	0.084	0.117

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.
Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

We run the same regression specifications with wheat yield measured in quintals of output per hectare replacing the dependent variable. The results are presented in Table 4-5. The IR between wheat farm size and yield is maintained for small-scale farms. The magnitudes of the IR, however, seem to be lower than among maize farms. This is perhaps expected as Figure 4-1b shows wheat yields decreasing more slowly than maize yields among smallholder farmers. There is no significant relationship between crop area and yield among medium-scale wheat farmers. In contrast, there is strong IR among large-scale wheat farms. This relationship endures after controlling for use of different chemicals, labor, and experience with crop shocks. Note, however, that increasing total landholding size while keeping wheat crop area fixed is associated with higher wheat yields for both small and large-scale farms. This suggests that farms that allocate larger land to crops other than wheat increase their wheat yields better than those that allocate a larger proportion of their landholding to wheat. This may be because the inputs used for other crops may complement the wheat production process for small and large-scale farms.

Table 4-5: IR estimates for wheat yield per ha: village fixed effects

	Small (<10 ha)		Medium (10 - 50 ha)		Large (>50 ha)	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.141***	0.133**	-0.269	-0.013	0.956***	0.803**
	(0.054)	(0.052)	(0.421)	(0.389)	(0.307)	(0.331)
Ln(crop area in ha)	-0.279***	-0.292***	-0.402	-0.243	-0.659***	-0.609**
	(0.041)	(0.041)	(0.436)	(0.367)	(0.254)	(0.253)
Arcsinh(chemical fertilizer use in quintals per ha)	0.216***	0.194***	1.197***	1.572***	38.329	48.154
	(0.045)	(0.044)	(0.386)	(0.172)	(42.282)	(46.365)
Arcsinh(No. of workers per ha)	0.090**	0.080**	-0.203	-1.107***	0.418***	0.329**
	(0.038)	(0.037)	(0.341)	(0.319)	(0.151)	(0.143)
Used pesticides		0.122		0.173		0.743
		(0.125)		(0.557)		(0.528)
Used fungicides		0.231*		-0.779*		-0.053
		(0.133)		(0.465)		(0.257)
Used herbicides		0.116*		-1.147*		-1.060*
		(0.062)		(0.591)		(0.545)
Used improved seeds		0.181***		0.513		-0.627***
		(0.066)		(0.533)		(0.175)
Experienced crop shocks		-0.222***		-1.078***		-0.272
		(0.062)		(0.327)		(0.289)
Year=2014[a]	0.093*	0.048	0.668	-0.065	0.512	0.384
	(0.056)	(0.054)	(0.482)	(0.462)	(0.472)	(0.493)
Constant	1.428***	1.475***	4.047**	5.765***	-0.228	1.796
	(0.121)	(0.124)	(1.911)	(1.825)	(1.255)	(1.197)
Number of observations	1,523	1,523	39	39	154	150
R2	0.126	0.153	0.440	0.760	0.252	0.335

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey. Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.

We also investigate the IR between productivity and farm size using teff yield as dependent variable. The regression results are presented in Table 4-6. The IR is maintained across all three farm size categories. However, the results for medium and large-scale farms are tentative as relatively few farms plant this crop. As discussed before, medium and large-scale farms are more export-oriented and the government of Ethiopia has put restrictions on exporting of unprocessed teff grains during the survey periods. As in the case of wheat farms, teff yields also respond positively for farms that allocate additional land to crops other than teff. The complementarity between teff and production of other crops may be driving this result.

Table 4-6: IR estimates for teff yield per ha: village fixed effects

	Small (<10 ha)		**Medium (10 - 50 ha)**		**Large (>50 ha)**	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.224***	0.219***	0.694**	0.607**	-0.131	-0.020
	(0.045)	(0.045)	(0.299)	(0.261)	(0.217)	(0.165)
Ln(crop area in ha)	-0.406***	-0.405***	-0.471**	-0.394*	-0.305*	-0.214
	(0.034)	(0.035)	(0.201)	(0.225)	(0.159)	(0.161)
Arcsinh(chemical fertilizer use in quintals per ha)	0.233***	0.230***	3.848***	3.154***	-17.247	6.397
	(0.044)	(0.043)	(0.623)	(1.009)	(15.670)	(24.348)
Arcsinh(No. of workers per ha)	0.202***	0.195***	0.013	-0.058	-0.043	-0.066
	(0.032)	(0.032)	(0.088)	(0.092)	(0.056)	(0.090)
Used pesticides		0.070		0.281		-0.624
		(0.111)		(0.411)		(0.797)
Used fungicides		0.012		-		-0.126
		(0.122)				(0.657)
Used herbicides		0.093*		0.699**		-0.139
		(0.056)		(0.319)		(0.365)
Used improved seeds		-0.094		0.186		-0.080
		(0.083)		(0.322)		(0.245)
Experienced crop shocks		-0.145**		-0.772		0.130
		(0.057)		(0.510)		(0.276)
Year=2014[a]	0.213***	0.175***	-0.310	0.180	-1.057***	-1.030***
	(0.053)	(0.050)	(0.499)	(0.482)	(0.345)	(0.364)
Constant	0.422***	0.484***	0.164	0.221	3.966***	3.194***
	(0.111)	(0.112)	(0.929)	(0.811)	(1.492)	(1.191)
Number of observations	2,201	2,201	66	65	121	110
R2	0.214	0.222	0.498	0.602	0.209	0.226

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.
Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse

hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

The relationships between sorghum yield and crop area and other controls are presented in Table 4-7. The IR is maintained for small and large-scale farms while there is no relationship between crop area and yield among medium-scale farms. This result is robust to inclusion of various farm inputs as controls. As before, there appears to be complementarity between sorghum yields and allocation of additional land to other crops (see coefficient on Ln(holding size in ha) in Table 4-7). Surprisingly, the amount of chemical fertilizer used is negatively associated with sorghum yield among large-scale farms after controlling for other inputs. The data shows that large-scale farms are already using very small amounts of fertilizer per unit of land (see Table 4-3). This may explain why there is no statistical relationship between chemical fertilizer use and yield for three of the five crops considered (i.e., for wheat, teff, and sesame). Positive relationship is observed for only maize farms while it is negative for sorghum farms among large-scale operators.

Table 4-7: IR estimates for sorghum yield per ha: village fixed effects

	Small (<10 ha)		Medium (10 - 50 ha)		Large (>50 ha)	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.258***	0.254***	0.434**	0.454**	0.213***	0.200***
	(0.048)	(0.049)	(0.214)	(0.203)	(0.040)	(0.042)
Ln(crop area in ha)	-0.417***	-0.414***	-0.135	-0.098	-0.207***	-0.184***
	(0.042)	(0.042)	(0.083)	(0.085)	(0.029)	(0.028)
Arcsinh(chemical fertilizer use in quintals per ha)	0.001	0.008	0.124	-0.358	-4.918***	-4.678***
	(0.078)	(0.076)	(0.830)	(1.288)	(1.716)	(1.648)
Arcsinh(No. of workers per ha)	0.220***	0.216***	0.120**	0.107*	0.032	0.041
	(0.043)	(0.045)	(0.052)	(0.057)	(0.044)	(0.036)
Used pesticides		-0.089		0.111		-0.334**
		(0.151)		(0.290)		(0.134)
Used fungicides		0.049				0.252***
		(0.124)				(0.052)
Used herbicides		0.049		-0.102		0.024
		(0.086)		(0.098)		(0.071)
Used improved seeds		-0.238		-0.406		0.170*
		(0.230)		(0.316)		(0.096)
Experienced crop shocks		-0.158***		-0.587***		-0.495***
		(0.060)		(0.112)		(0.065)
Year=2014[a]	0.237***	0.194***	0.235	0.180	0.266***	0.227***
	(0.066)	(0.065)	(0.255)	(0.244)	(0.082)	(0.087)
Constant	0.922***	1.027***	1.477	1.938*	2.507***	2.867***
	(0.126)	(0.139)	(1.130)	(1.109)	(0.174)	(0.200)
Number of observations	1,818	1,818	398	392	1,115	1,084
R2	0.186	0.192	0.058	0.150	0.097	0.164

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.
Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

The last IR that we investigate is between sesame yields and crop area allocation decisions. The results are presented in Table 4-8. Sesame is one of the major crops grown for export in Ethiopia.

Indeed, the number of large-scale farms that grow the crop are more than three times the number of small-scale sesame farmers in our sample.

The results in Table 4-8 show that the IR endures for small-scale farms and to a lesser extent for large-scale operators. As before, increasing the total landholding by allocating land to crops other than sesame crops is associated with increased sesame yields.

Table 4-8: IR estimates for sesame yield per ha: village fixed effects

	Small (<10 ha)		**Medium (10 - 50 ha)**		**Large (>50 ha)**	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.325**	0.318**	-0.187	-0.158	0.146**	0.151**
	(0.126)	(0.126)	(0.138)	(0.139)	(0.060)	(0.060)
Ln(crop area in ha)	-0.420***	-0.403***	-0.105	-0.098	-0.036	-0.063*
	(0.077)	(0.078)	(0.111)	(0.110)	(0.036)	(0.037)
Arcsinh(chemical fertilizer use in quintals per ha)	0.172	0.158	-1.675***	-1.490**	-0.680	-0.782
	(0.254)	(0.216)	(0.573)	(0.600)	(1.825)	(1.534)
Arcsinh(No. of workers per ha)	0.207**	0.206**	0.023	0.036	-0.027	-0.026
	(0.087)	(0.089)	(0.046)	(0.046)	(0.029)	(0.029)
Used pesticides		-0.412		0.116		0.359***
		(0.329)		(0.133)		(0.101)
Used fungicides		-		-0.078		0.199
				(0.109)		(0.240)
Used herbicides		-0.226		-0.002		0.399***
		(0.145)		(0.320)		(0.119)
Used improved seeds		0.386		0.168		-0.076
		(0.355)		(0.180)		(0.088)
Experienced crop shocks		-0.391***		-0.545***		-0.307*
		(0.079)		(0.126)		(0.168)
Year=2014[a]	-0.062	-0.070	1.443***	1.442***	1.275***	1.263***
	(0.136)	(0.126)	(0.154)	(0.156)	(0.310)	(0.282)
Constant	0.164	0.375	1.788***	2.116***	0.454	0.756*
	(0.333)	(0.328)	(0.514)	(0.451)	(0.388)	(0.400)
Number of observations	353	353	472	461	1,348	1,322
R2	0.150	0.191	0.519	0.548	0.385	0.411

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.

Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

4.4. Robustness Checks

We check for the robustness of the IR estimates that we reported thus far by replacing village fixed effects with district fixed effects. In Ethiopia, the 'kebele' or village is the lowest administrative unit and consists of an average of 5,000 individuals. Districts or 'woredas' are the next higher administrative units and are composed of about 26 kebeles on average (Yilmaz and Venugopal, 2008). Districts are relatively more autonomous and direct agricultural development programs within their constituents.

The results of the robustness checks with district fixed effects are presented in Tables 4-1A to 4-5A in the Appendix. The directional relationship between crop area and yield are largely similar whether we use village or district fixed effects. More specifically, for maize, wheat, and teff crops, the IR estimates for each of the farm-size categories with village fixed effects have similar signs to their counterparts that use district fixed effects. The only exceptions are among medium-scale sorghum and sesame farms and large-scale sesame farms. With district fixed effects, the IR is observed among medium-scale farms for sorghum and sesame crops (specifications m3 and m4 in Tables 4-4A and 4-5A). By contrast, we found no relationship when village fixed effects are used (specifications m3 and m4 in Tables 4-7 and 4-8). Furthermore, IR is found among large-scale sesame farms when village fixed effects are used, which we did not find in our robustness checks (specification m6 in Tables 4-8 and 4-5A). Note, however, that the IR is significant only at 10% significance level in our main result in Table 4-8.

Overall, our robustness checks suggest that except for few estimates, the main results we reported and discussed so far are robust to different specifications and levels of administrative units as fixed effects.

4.4. Conclusion and Policy Implication

This study investigates the inverse relationship between farm-size and productivity over large variation in cultivated areas and for each of the major grain crops grown in the country. To our knowledge, this paper is the first to examine this relationship by including small, medium, and large-scale farms in the sample. Most other studies focus on small-scale farming.

Overall, our results confirm the empirical regularity of the IR between farm-size and productivity for small-scale agriculture that has been well documented in the literature. This is true for each of the five major crops considered in this study. The results for medium- and large-scale farms are mixed. For medium-scale farms, we found no relationship between crop area and productivity for all the crops except Teff. For large-scale farms, the IR is maintained for all the crops except maize. Furthermore, allocating additional land to crops other than those under consideration is associated with higher yield for the crop studied. This is perhaps because of the complementarity achieved through diversification of the crops grown. These results are largely robust to the inclusion or exclusion of other inputs as controls and whether we use village or district fixed effects.

These results do not mean, however, that small-scale farms should be consolidated so that all farms are medium-scale as they seem more efficient (Muyanga and Jayne 2019). The implication on landlessness and gainful employment both on and off the farm should also be considered among others.

References:

Abadie, A., and G. Imbens. 2016. Matching on the Estimated Propensity Score. *Econometrica* 84(2):781-807.

Abay. K.A., L. Bevis., and C.B. Barrett. 2019. "Measurement Error Mechanisms Matter: Agricultural Intensification with Farmer Misperceptions and Misreporting." NBER Working Paper No. 26066.

Akaakohol, M. A., and G. C. Aye. 2014. "Diversification and Farm Household Welfare in Makurdi, Benue State, Nigeria." *Development Studies Research* 1(1): 168–175.

Ali, D. A., and K. Deininger. 2015. "Is There a Farm Size–Productivity Relationship in African Agriculture? Evidence from Rwanda." Land Economics, 91 (2): 317–343.

Angrist, J.D., and J.S. Pischke. 2009. Mostly Harmless Econometrics; An Empiricist's Companion. Princeton University Press.

Arndt, C., K. Pauw, and J. Thurlow. 2015. The Economy-Wide Impacts and Risks of Malawi's Farm Input Subsidy Program. *American Journal of Agricultural Economics 98(3): 962-980*.

Assuncao, J. J., and Braido L. HB. 2007. "Testing household-specific explanations for the inverse productivity relationship." *American Journal of Agricultural Economics*, 89(4): 980-990.

Barrett, C. B., M. F. Bellemare, and J. Y Hou. 2010. "Reconsidering conventional explanations of the inverse productivity-size relationship." *World Development*, 38(1): 88{97.

Barrett, C. B. 1996. "On price risk and the inverse farm size-productivity relationship." *Journal of Development Economics*, 51(2): 193-215.

Bellora, C., É. Blanc, J. M. Bourgeon, and E. Strobl. 2017. "Estimating the Impact of Crop Diversity on Agricultural Productivity in South Africa." National Bureau of Economic Research (NBER) Working Paper No. 23496. Cambridge, MA.

Benin, S., M. Smale, J. Pender, B. Gebremedhin, and S. Ehui. 2004. "The Economic Determinants of Cereal Crop Diversity on Firms in the Ethiopian Highlands." *Agricultural Economics* 31:197–208.

Benjamin, D. 1995. "Can unobserved land quality explain the inverse productivity relationship?" *Journal of Development Economics*, 46(1): 51-84.

Benson, T., A. Erman, and B. Baulch. 2018. Change and Rigidity in Youth Employment Patterns in Malawi. Book Chapter on Malawi Youth and Employment. Washington D.C.: IFPRI (International Food Policy Research Institute).

Bevis, Leah EM, and C. B. Barrett. 2016. Close to the Edge: Do Behavioral Explanations Account for the Inverse Productivity Relationship? Working Paper.

Bezner-Kerr, R., S. Snapp, M. Chirwa, L. Shumba, and R. Msachi. 2007. "Participatory Research on Legume Diversification with Malawian Smallholder Farmers for Improved Human Nutrition and Soil Fertility." *Experimental Agriculture* 43: 437–453.

Carletto, C., S. Savastano, and A. Zezza. 2013. “Fact or artifact: the impact of measurement errors on the farm size-productivity relationship." *Journal of Development Economics*, 103: 254-261.

Carter, M. R. 1984. “Identification of the inverse relationship between farm size and productivity: an empirical analysis of peasant agricultural production." *Oxford Economic Papers*, 131-145.

Central Statistical Agency and World Bank. 2017. “LSMS—Integrated Surveys on Agriculture Ethiopia Socioeconomic Survey (ESS) 2015/2016” Report on LSMS-ISA Ethiopia 2015/16.

Central Statistical Agency. 2015. “Large and medium scale commercial farms sample survey 2014/15 (2007 EC): Results at country and regional level volume VII.” Statistical report on area and production of crops, and farm management practices.

Chen, Z., W. E. Huffman, and S. Rozelle. 2011. “Inverse Relationship between Productivity and Farm Size: The Case of China.” *Contemporary Economic Policy* 29 (4): 580–92.

Chirwa, E. W. 2010. “Assessment of Maize Trade and Market Policy Interventions in Malawi.” In *Food Security in Africa Market and Trade Policy for Staple Foods in Eastern and Southern Africa*, edited by A. Sarris and J. Morrison.

Chirwa, E. W., M. M. Matita, P. M. Mvula, and A. R. Dorward. 2011. Impacts of the Farm Input Subsidy Programme in Malawi. Paper prepared for Malawi Government/DFID Evaluation of Malawi Farm Input Subsidy Programme. School of Oriental and African Studies, University of London.

Chirwa, E. W., Matita, M. M., Mvula, P.M, and W. Mhango. 2016. Evaluation of the 2015/16 Farm Input Subsidy Program in Malawi: 2015/16 Reforms and their Implications. Final Report. Undertaken for the Ministry of Agriculture, Irrigation and Water Development

Chirwa, E.W., and A.R. Dorward. 2013. Agricultural Input Subsidies in Low Income Countries and the Malawi experience. Oxford University Press, Oxford.

Coelli, T., and E. Fleming. 2004. “Diversification Economies and Specialization Efficiencies in a Mixed Food and Coffee Smallholder Farming System in Papua New Guinea.” *Agricultural Economics* 31: 229–239.

Collier, P., and S. Dercon. 2014. “African Agriculture in 50 Years: Smallholders in a Rapidly Changing World?” *World Development* 63: 92–101.

Collier, Paul, and Anthony J. Venables. 2012. “Land Deals in Africa: Pioneers and Speculators.” Discussion Paper 8644. London: Centre for Economic Policy Research.

Deaton, A. 1988. Quality, quantity, and Spatial variation of price. *American Economic Review* 78(3): 418-430.

Desiere, S., and D. Jolliffe. 2018. “Land productivity and plot size: Is measurement error driving the inverse relationship?” *Journal of Development Economics 130: 84-98.*

Crop Trust. 2018. "Crop Diversity: Why it Matters." Accessed from https://www.croptrust.org/our-mission/crop-diversity-why-it-matters/?print=true.

Deininger, K., and D. Beyerlee. 2012. "The Rise of Large Farms in Land Abundant Countries: Do They Have a Future?" *World Development*, 40(4), 701–714.

Druilhe, Z., and J. Barreiro-Hurlé. 2012. Fertilizer subsidies in sub-Saharan Africa. FAO ESA working paper No. 12-04.

Dionne, K.Y., and J. Horowitz. 2013. The political Effects of Anti-Poverty Initiatives: An Analysis of Malawi's Agricultural Input Subsidy Program. Working Paper.

Dorward, A. R., and Chirwa E. W. 2015. "Crowding out, diversion, and benefit/cost assessments in fertilizer subsidy programs in sub-Saharan Africa: a comment on Jayne, T.S., Mather, D., Mason, N., Ricker-Gilbert, J., 2013. How do fertilizer subsidy programs affect total fertilizer use in sub-Saharan Africa? Crowding out, diversion, and benefit/cost assessments." *Agricultural Economics 46 (6): 739–744.*

Dorward A. R., and E.W. Chirwa. 2013. Targeting in the Farm Input Subsidy Programme in Malawi: Issues and Options. Working paper 066. Future agricultures.

Ecker, O. 2018. "Agricultural Transformation and Food and Nutrition Security in Ghana: Does Farm Production Diversity (still) Matter for Household Dietary Diversity?" *Food Policy* 79: 271-282.

Feder, G. 1985. "The relation between farm size and farm productivity: The role of family labor, supervision and credit constraints." *Journal of Development Economics*, 18(2): 297-313.

Foster, A., and M.R. Rosenzweig. 2017. Are There Too Many Farms in the World? Labor-Market Transaction Costs, Machine Capacities and Optimal Farm Size. NBER Working Paper 23909.

Fry K., R. Firestone, and N.M. Chakraborty. 2014. Measuring Equity with Nationally Representative Wealth Quintiles. Washington, DC: PSI.

Gelaw, A. M., B. R. Singh, and R. Lal. 2015. "Soil Quality Indices for Evaluating Smallholder Agricultural Land Uses in Northern Ethiopia" *Sustainability*, (7): 2322-2337.

Gourlay, S., T. Kilic, and D. Lobell. 2017. "Could the Debate Be Over? Errors in Farmer-Reported Production and Their Implications for the Inverse Scale-Productivity Relationship in Uganda" World Bank Policy Research Working Paper 8192.

Government of Ethiopia. 2018. "Agricultural sample survey 2017/18 (2010 E.C.) Volume I. Report on Area and production of major Crops (private peasant holdings, meher season)." Central statistical agency.

Government of Malawi. 2015. Malawi - Integrated Household Panel Survey 2013. National Statistical Office.

Haile, H. B.. 2016. “Large and medium scale commercial farms annual Survey, the domino effect of World Bank intervention, challenges and innovative approaches: The experience of Ethiopia.” Presentation Paper for World Bank Technical Meeting.

Heltberg, R. 1998. “Rural market imperfections and the farm size-productivity relationship: Evidence from Pakistan." *World Development*, 26(10): 1807-1826.

Henderson, H. 2015. “Considering Technical and Allocative Efficiency in the Inverse Farm Size-Productivity Relationship." *Journal of Agricultural Economics*, 66(2): 442-469.

Holden, S., and R. Lunduka. 2010. Impacts of the fertilizer subsidy programme in Malawi: targeting, household perceptions and preferences. Noragric Report.

Houssou, N. and K. Droppelmann. 2013. How best to target agricultural subsidies? The Case for an Indicator-Based Targeting System in Malawi. IFPRI policy note 15. Malawi Strategy Support Program.

International Food Policy Research Institute (IFPRI). 2014. “Does Irrigation Have an Impact on Food Security and Poverty: Evidence from Bwanje Valley Irrigation Scheme in Malawi”. MaSSP Working Paper 4. Washington D.C.: IFPRI.

Islam, S., and M. R. Ullah. 2012. “The Impacts of Crop Diversity in the Production and Economic Development in Bangladesh.” *International Journal of Economics and Finance* 4 (6): 169–180.

Jacoby, H. 2016. Smart Subsidy? Welfare and Distributional Consequences of Malawi’s FISP. Background paper for the book “Reaping Richer Returns: Public Spending Priorities for African Agriculture Productivity Growth. Africa Development Forum series.” Goyal, Aparajita, and John Nash (eds). 2017. Washington, DC: World Bank.

Jayne T. S., D. Mather, N.M. Mason, J. Ricker-Gilbert, and Crawford E.W. 2015. “Rejoinder to the comment by Andrew Dorward and Ephraim Chirwa on Jayne, T. S., D. Mather, N. Mason, and J. Ricker-Gilbert. 2013. How do fertilizer subsidy program affect total fertilizer use in sub-Saharan Africa? Crowding out, diversion, and benefit/cost assessments. Agricultural Economics, 44(6), 687–703.” *Agricultural Economics 46 (6): 745–755.*

Jayne, T.S., D. Mather, N.M. Mason, and J. Ricker-Gilbert. 2013. “How do fertilizer subsidy programs affect total fertilizer use in sub-Saharan Africa? Crowding out, diversion, and benefit/cost assessments.” *Agricultural Economics 44: 687-703.*

Jayne, T.S., and S. Rashid. 2013. “Input subsidy programs in sub-Saharan Africa: a synthesis of recent evidence.” *Agricultural Economics*, 44: 547–562.

Jones, A. 2017. “On-Farm Crop Species Richness is Associated with Household Diet Diversity and Quality in Subsistence- and Market-Oriented Farming Households in Malawi.” *The Journal of Nutrition* 147: 86–96.

Jones, A.D, A. Shrinivas, and R. Bezner-Kerr. 2014. “Farm Production Diversity is Associated with Greater Household Dietary Diversity in Malawi: Findings from Nationally Representative Data.” *Food Policy* 46: 1–1.

Kagin, J., E. Taylor, and A. Yunez-Naude. 2016. “Inverse Productivity or Inverse Efficiency? Evidence from Mexico." *The Journal of Development Studies*, 1-16.

Kankwamba, H., M. Kadzamira, and K. Pauw. 2018. “How Diversified is Cropping in Malawi? Patterns, Determinants and Policy Implications.” *Food Security* 10: 323–338.

Kelly, V., E. Crawford, and J. Ricker-Gilbert. 2011 . The new generation of African fertilizer subsidies: panacea or Pandora’s box? Policy Synthesis 87. East Lansing, Michigan: Michigan State University/United States Agency for International Development Food Security III Cooperative Agreement (GDGA-00- 000021-00).

Koppmair, S., M. Kassie, and M. Qaim. 2016. “Farm Production, Market Access and Dietary Diversity in Malawi.” *Public Health Nutrition* 20 (2): 325–335.

Lamb, R. L. 2003. “Inverse productivity: Land quality, labor markets, and measurement error." *Journal of Development Economics*, 71(1): 71-95.

Leuven, E., and B. Sianesi. 2012. PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing.

Lim, S. 2018. “Risk Aversion, Crop Diversity, and Food Security.” Working Paper. Department of Applied Economics. University of Minnesota. Accessed from https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=CSAE2018&paper_id=1196

Lin, B.B. 2011. “Resilience in Agriculture through Crop Diversification: Adaptive Management for Environmental Change.” *BioScience* 61 (3): 183–193.

Magurran, A.E. 2003. *Measuring Biological Diversity.* 2nd edition. Oxford, U.K: Wiley-Blackwell Science Ltd.

Malawi Vulnerability Assessment Committee. 2005. Food Security Update Report: Malawi. http://www.fews.net/docs/Publications/1000878.pdf.

Malik, Z.A., and M. C. Nautiyal. 2016. “Species Richness and Diversity along the Altitudinal Gradient in Tungnath, the Himalayan Benchmark Site of HIMADRI.” *Tropical Plant Research* 3 (2): 396–407.

Makate, C., R. Wang, M. Makate, and N. Mango. 2016. “Crop Diversification and Livelihoods of Smallholder Farmers in Zimbabwe: Adaptive Management for Environmental Change.” *SpringerPlus* 1135 (5): 1–18.

Mango, N., C. Makate, L. Mapemba, and M. Sopo. 2018. “The Role of Crop Diversification in Improving Household Food Security in Central Malawi.” *Agriculture and Food Security* 7 (7): 1–10.

Mason, N. and J. Ricker-Gilbert. 2013. "Disrupting Demand for Commercial Seed: Input Subsidies in Malawi and Zambia." *World Development 45: 75-91*.

Mason, N., T.S. Jayne, and R. Mofya-Mukuka. 2013. "Zambia's input subsidy programs." *Agricultural Economics* 44: 613–628.

M'Kaibi, F. K., N. P. Steyn, S. A. Ochola, and L. D. Plessis. 2017. "The Relationship between Agricultural Biodiversity, Dietary Diversity, Household Food Security, and Stunting of Children in Rural Kenya." *Food Science & Nutrition* 5 (2): 243–254.

Matchaya, G. C., A. Phiri, P. Chilonda, and E. Musaba. 2014. Agricultural Growth Trends and Outlook Report: Trends in Agricultural Sector Performance, Growth and Poverty in Malawi, ReSAKSS-SA Annual Trends and Outlook Report 2012. Pretoria, South Africa: International Food Policy Research Institute (IFPRI) and the International Water Management Institute (IWMI).

Mazunda, J., H. Kankwamba, and K. Pauw. 2015. "Food and Nutrition Security Implications of Crop Diversification in Malawi's Farm Households." In *Mapping the linkages between agriculture, food security and nutrition in Malawi.* Chapter 5, 44–49. Lilongwe, Malawi; and Washington, D.C.: IFPRI (International Food Policy Research Institute). http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/129902

Messina, J., B. Peter, S. Snapp. 2017." Re-evaluating the Malawian farm input subsidy programme." *Nature Plants 3*: 1–8.

Minten, B., and A.S. Taffesse. 2018. Teff love: Ethiopia's staple crop requires a big push. Thomson Reuters Foundation News. http://news.trust.org/item/20180821141610-h3zpe.

Morris, M., L. Ronchi, and D. Rohrbach. 2009. Building sustainable fertilizer markets in Africa. In: International Livestock Research Institute (ILRI) (ed.) Towards Priority Actions for Market Development for African Farmers. Nairobi: ILRI.

Morris, M., V. Kelly, R. Kopicki, and D. Byerlee. 2007. Fertilizer use in African agriculture: Lessons Learned and Good Practice Guidelines. World Bank, Washington, DC.

Muyanga, M., and T.S. Jayne. 2019. "Revisiting the Farm Size-Productivity Relationship Based on a Relatively Wide Range of Farm Sizes: Evidence from Kenya." *American Journal of Agricultural Economics*, aaz003, https://doi.org/10.1093/ajae/aaz003.

Namonje-Kapembwa, T., R. BlackT.S. Jayne. 2015. Does late delivery of subsidized fertilizer affect smallholder productivity and production? Working paper 97. Indaba Agricultural Policy Research Institute (IAPRI).

Nguyen, H.Q. 2017. "Analyzing the Economies of Crop Diversification in Rural Vietnam using an Input Distance Function." *Agricultural Systems* 153: 148–156.

Nhamo, N., G. Kyalo, and V. Dinheiro. 2014. "Chapter Five - Exploring Options for Lowland Rice Intensification under Rain-fed and Irrigated Ecologies in East and Southern Africa: The

Potential Application of Integrated Soil Fertility Management Principles." *Advances in Agronomy* 128: 181-219.

Njeru, E.M. 2013. "Crop Diversification: A Potential Strategy to Mitigate Food Insecurity by Smallholders in Sub-Saharan Africa." *Journal of Agriculture, Food Systems, and Community Development* 3 (4): 63–69.

Oxfam. 2016. El Nino drought forces Malawi to declare a food emergency: urgent action needed. https://www.oxfam.org/en/pressroom/pressreleases/2016-04-18/el-nino-drought-forces-malawi-declare-food-emergency-urgent.

PDNA (Post-Disaster Needs Assessment). 2017. "Malawi Drought 2015–2016: Post-Disaster Needs Assessment."

Peter, G., and A. Runge-Metzger. 1994. "Monocropping, Intercropping or Crop Rotation? An Economic Case Study from the West African Guinea Savannah with Special Reference to Risk." *Agricultural Systems* 45 (2): 123–143.

Ricker-Gilbert, J., and T.S. Jayne. 2016. "Estimating the enduring effects of fertilizer subsidies on commercial fertilizer demand and maize production: panel data evidence from Malawi." *Journal of Agricultural Economics*. doi: 10.1111/1477-9552.12161.

Ricker-Gilbert, J. 2014. "Wage and employment effects of Malawi's fertilizer subsidy program." *Agricultural Economics 45(3): 337-353.*

Ricker-Gilbert, J., N. Mason, F.A. Darko, and S.T. Tembo. 2013. "What are the effects of input subsidy programs on maize prices? Evidence from Malawi and Zambia." *Agricultural Economics 44(6): 671-686*.

Ricker-Gilbert, J., T.S. Jayne, and E. Chirwa. 2011. "Subsidies and crowding out: A double-hurdle model of fertilizer demand in Malawi." *American Journal of Agricultural Economics* 93(1): 26-42.

Sichoongwe, K., L. Mapemba, D. Ng'ong'ola, and G. Tembo. 2014. "The Determinants and Extent of Crop Diversification among Smallholder Farmers: A Case Study of Southern Province, Zambia. International Food Policy Research Institute." Working Paper 5. Malawi Strategy Support Program.

Simpson, E. H. 1949. "Measurement of Diversity." *Nature*: 163, 688.

Snapp, S., and M. Fisher. 2015. "'Filling the Maize Basket' Supports Crop Diversity and Quality of Household Diet in Malawi." *Food Security* 7: 83–96.

Sachs, J. 2012. How Malawi Fed Its Own People. New York Times. https://www.nytimes.com/2012/04/20/opinion/how-malawi-fed-its-own-people.html

Sahley, C., R. Groelsma, T. Marchione, and D. Nelson. 2005. The Governance Dimension of Food Security in Malawi. Lilongwe. USAID, Malawi.

Sen, A. K. 1966. “Peasants and Dualism with or without Surplus Labor." *Journal of Political Economy*, 74(5): 425-450.

Shegro, A., N. G. Shargie, A. van Biljon, and M. T. Labuschagne. 2012. “Diversity in Starch, Protein and Mineral Composition of Sorghum Landrace Accessions from Ethiopia.” *Journal of Crop Science and Biotechnology* 15(4): 275-280.

Walsh, O. S. 2006. Effect of Delayed Nitrogen Fertilization on Corn Grain Yields. M.S. thesis, Oklahoma State University.

Weigel, R., T. Koellner, P. Poppenborg, and C. Bogner. 2018. “Crop Diversity and Stability of Revenue on Farms in Central Europe: An Analysis of Big Data from a Comprehensive Agricultural Census in Bavaria.” *PLoS ONE* 13 (11): 1–18.

Wooldridge, J. 2010. *Econometric Analysis of Cross-Section and Panel Data*. 2nd Edition. The MIT Press Cambridge, Massachusetts London, England.

World Bank. 2016. “Malawi Economic Monitor (MEM), October 2016: Emerging Stronger.” Washington, D.C.

———. 2018a. *Malawi’s Progress Towards Shared Prosperity Since 2004.* World Bank’s Poverty and Equity Global Practice Report. Washington, D.C.

———. 2018b. *Malawi - Systematic Country Diagnostic: Breaking the Cycle of Low Growth and Slow Poverty Reduction*. Washington, D.C.

Xu, Z., Z. Guan, T.S. Jayne, and R. Black. 2009. “Factors influencing the profitability of fertilizer use on maize in Zambia.” *Agricultural Economics* 40: 437–446.

Yilmaz, S., and V. Venugopal. 2008. “Local Government Discretion and Accountability in Ethiopia.” International Studies Program Working Paper 08-38.

Chapter 2 Appendix

A2-1. Derivation of consumer surplus from regression equation of fertilizer demand

The fitted fertilizer demand equation of the population regression equation in equation (1) can be expressed as

$$\ln(\hat{f}_{ij}) = \alpha_j X_{ij} + \beta_j \ln(p_{ij})$$

$$-\!\!\rightarrow \hat{f}_{ij} = e^{(\alpha_j X_{ij} + \beta_j \ln(p_{ij}))}$$

$$-\!\!\rightarrow \hat{f}_{ij} = e^{(\alpha_j X_{ij})} e^{\beta_j \ln(p_{ij}))}$$

$$-\!\!\rightarrow \hat{f}_{ij} = e^{(\alpha_j X_{ij})} * {p_{ij}}^{\beta_j}$$

Integrating the above equation over two price intervals p_i^A and p_i^B and dropping the fertilizer type subscript j for brevity we get:

$$\int_{p_i^B}^{p_i^A} \widehat{f_i}\, dp_i = \int_{p_i^B}^{p_i^A} e^{(\alpha X_i)} * p_i^{\beta}\, dp_i$$

$$-\!\!\rightarrow \int_{p_i^B}^{p_i^A} \widehat{f_i}\, dp_i = e^{(\alpha X_i)} * \left(\frac{(p_i^A)^{\beta+1} - (p_i^B)^{\beta+1}}{\beta + 1} \right)$$

Table A2-1: Descriptive Statistics for Fertilizer Voucher Recipients and Non-recipients in 2013

	Voucher non-recipients		Voucher recipients		
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**|t test|**
Variables					**diff of means**
kg of NPK fertilizer acquired	18.67	43.30	53.05	47.18	34.38***
kg of urea fertilizer acquired	19.81	45.23	61.79	154.04	41.98***
Amount of land cultivated by HH (ha)	0.54	0.60	0.79	0.63	0.26***
Wealth Index	-0.60	3.01	0.71	0.44	1.31***
Farm credit org in village (=1 if yes)	0.39	0.49	0.39	0.49	-0.00
Household size	5.84	2.38	6.26	2.28	0.42***
Female headed HH (=1 if yes)	0.21	0.41	0.21	0.41	-0.00
Age of HH head	41.24	13.72	46.38	14.87	5.14***
Years of education for HH head	6.3	4.35	5.00	3.67	-1.30***
Networked with village head or traditional authority (=1 if yes)	0.02	0.13	0.35	0.48	0.33***
Received advice on fertilizer use (=1)	0.39	0.49	0.55	0.5	0.16***
KM from HH to nearest agricultural market	21.99	15.97	25.34	14.71	3.35***
Log (elevation in meters)	6.67	0.62	6.76	0.36	0.09***
Log (annual precipitation in mm)	6.73	0.10	6.73	0.1	0.01
HH experienced drought (=1 if yes)	0.28	0.45	0.34	0.47	0.06***
HH experienced flooding (=1 if yes)	0.12	0.32	0.17	0.38	0.05***
HH experienced irregular rain (=1 if yes)	0.43	0.49	0.53	0.5	0.11***
HH received assistance through safety net (=1 if yes)	0.36	0.48	0.50	0.50	0.14***
Soil quality index	0.01	1.42	-0.02	1.40	-0.03
Number of households in sample	1,271				637

Note: * significant at 10%; ** significant at 5%; *** significant at 1%
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-2: Household Fixed Effects Estimates of Demand for Commercial NPK Fertilizer for Voucher Non-recipients

	Dependent Variable: Arcsinh (kg of commercial NPK fertilizer acquired per farm)					
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Arcsinh (real price of fertilizer in Kw/kg)	-0.791***	-0.851***	-0.763***	-0.783***	-0.784***	-0.794***
	(0.198)	(0.209)	(0.223)	(0.234)	(0.236)	(0.235)
Wealth Index			0.049***	0.052***	0.052***	0.051***
			(0.017)	(0.016)	(0.017)	(0.016)
Arcsinh (Amount of land cultivated by HH in ha)			1.556***	1.550***	1.553***	1.571***
			(0.268)	(0.264)	(0.265)	(0.265)
Log (Maize price in MK/kg)			0.245	0.271	0.284	0.293
			(0.188)	(0.186)	(0.188)	(0.187)
Number of working age (15 to 65) HH members		0.010	-0.011	-0.012	-0.013	-0.008
		(0.067)	(0.061)	(0.060)	(0.060)	(0.061)
Female headed HH (=1 if yes)		0.066	0.052	0.065	0.058	0.093
		(0.126)	(0.132)	(0.140)	(0.141)	(0.137)
Age of HH head		0.013	0.010	0.009	0.009	0.009
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Years of education for HH head		0.023	0.033	0.041*	0.041*	0.041*
		(0.024)	(0.025)	(0.024)	(0.024)	(0.024)
Received advice on fertilizer use (=1)			0.082	0.080	0.081	0.083
			(0.125)	(0.124)	(0.123)	(0.123)
Farm credit org in village (=1 if yes)			-0.130	-0.142	-0.133	-0.129
			(0.133)	(0.138)	(0.142)	(0.137)
Log (KM from HH to nearest agricultural market)			-0.024	0.090	0.093	-0.016
			(0.140)	(0.152)	(0.152)	(0.160)
Log (elevation in meters)				-0.814*	-0.808*	-0.814*
				(0.422)	(0.421)	(0.433)
Log (annual precipitation in mm)				0.096	0.116	0.106
				(0.285)	(0.289)	(0.285)
HH experienced irregular rain (=1 if yes)				0.116	0.121	0.114
				(0.115)	(0.113)	(0.114)
Nutrient content of soil has no or slight problem (=1 if yes)				-0.668	-0.662	-0.751
				(1.150)	(1.152)	(1.209)
				-1.284*	-1.286*	-1.452*

Nutrient content of soil has moderate problem (=1 if yes)				(0.749)	(0.748)	(0.766)
Nutrient retention ability of soil has no or slight problem (=1 if yes)				-	-	-
Nutrient retention ability of soil has moderate problem (=1 if yes)				-0.304	-0.294	-0.380
				(0.966)	(0.968)	(0.919)
Rooting condition is not or a slight constraint (=1 if yes)				0.065	0.092	0.391
				(0.737)	(0.739)	(0.724)
Rooting condition is a moderate constraint (=1 if yes)				-0.741	-0.736	-0.722
				(0.521)	(0.522)	(0.522)
Oxygen availability to roots is not or a slight constraint (=1 if yes)				-0.484	-0.449	-0.150
				(1.169)	(1.167)	(1.045)
Oxygen availability to roots is a moderate constraint (=1 if yes)				-1.102	-1.072	-0.708
				(0.926)	(0.927)	(0.790)
Soil toxicity is not or a slight constraint (=1 if yes)				-	-	-
Soil toxicity is a moderate constraint (=1 if yes)				-2.669*	-2.649*	-2.866*
				(1.535)	(1.544)	(1.666)
Workability of soil is not or a slight constraint (=1 if yes)				-0.146	-0.191	-0.692
				(0.778)	(0.776)	(0.771)
Workability of soil is a moderate constraint (=1 if yes)				0.411	0.395	0.125
				(0.650)	(0.650)	(0.640)
Central region (=1 if yes)					-0.743	
					(0.757)	
South region (=1 if yes)					-0.537	
					(0.801)	
Tropical warm and semiarid agro-ecological zone (=1)						0.901
						(0.559)
Tropical warm and sub-humid agro-ecological zone (=1)						0.074
						(0.502)
Tropical cool and semiarid agro-ecological zone (=1)						1.471*
						(0.819)
2016 year dummy (=1)	0.996***	1.037***	0.652**	0.631**	0.624**	0.627**
	(0.213)	(0.235)	(0.275)	(0.273)	(0.277)	(0.274)

Constant	5.389***	5.003***	3.104*	8.907*	9.201*	8.308*
	(1.098)	(1.245)	(1.731)	(4.862)	(4.851)	(4.756)
Unique observations	1,048	1,048	1,042	1,042	1,042	1,042
R-squared	0.026	0.034	0.116	0.132	0.133	0.136

Note: Robust standard errors clustered at Enumeration Area level in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; dependent variable, real price of fertilizer, and amount of land cultivated are transformed using inverse hyperbolic sine transformation. Fertilizer prices from both rounds are adjusted to average national prices from October to December 2015.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-3: Household Fixed Effects Estimates of Demand for Commercial Urea Fertilizer for Voucher Non- recipients

	Dependent Variable: Arcsinh (kg of commercial Urea fertilizer acquired per farm)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Arcsinh (real price of fertilizer in Kw/kg)	-0.755***	-0.833***	-0.846***	-0.832***	-0.832***	-0.835***
	(0.148)	(0.177)	(0.166)	(0.167)	(0.167)	(0.166)
Wealth Index			0.037**	0.035**	0.035**	0.036**
			(0.016)	(0.016)	(0.016)	(0.016)
Arcsinh (Amount of land cultivated by HH in ha)			1.525***	1.535***	1.536***	1.529***
			(0.292)	(0.293)	(0.295)	(0.293)
Log (Maize price in MK/kg)			0.146	0.162	0.171	0.160
			(0.176)	(0.177)	(0.179)	(0.179)
Number of working age (15 to 65) HH members		0.057	0.033	0.029	0.029	0.031
		(0.066)	(0.064)	(0.063)	(0.063)	(0.063)
Female headed HH (=1 if yes)		0.089	0.059	0.058	0.055	0.047
		(0.193)	(0.189)	(0.195)	(0.195)	(0.196)
Age of HH head		0.002	-0.000	0.000	0.000	0.001
		(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
Years of education for HH head		0.030	0.046	0.049*	0.049*	0.049*
		(0.028)	(0.030)	(0.029)	(0.029)	(0.029)
Received advice on fertilizer use (=1)			0.208*	0.214*	0.215*	0.210*
			(0.123)	(0.124)	(0.125)	(0.123)
Farm credit org in village (=1 if yes)			-0.282*	-0.282*	-0.277*	-0.282*
			(0.153)	(0.157)	(0.158)	(0.161)
			0.361**	0.379***	0.380***	0.411***

Log (KM from HH to nearest agricultural market)	(0.150)	(0.142)	(0.142)	(0.152)
Log (elevation in meters)		-0.150	-0.147	-0.010
		(0.644)	(0.642)	(0.627)
Log (annual precipitation in mm)		0.089	0.105	0.083
		(0.318)	(0.323)	(0.319)
HH experienced irregular rain (=1 if yes)		0.147	0.151	0.151
		(0.132)	(0.131)	(0.131)
Nutrient content of soil has no or slight problem (=1 if yes)		-1.190	-1.186	-1.599*
		(0.812)	(0.815)	(0.840)
Nutrient content of soil has moderate problem (=1 if yes)		-0.415	-0.416	-0.689
		(0.747)	(0.746)	(0.749)
Nutrient retention ability of soil has no or slight problem (=1 if yes)		-1.087		-0.338
		(1.244)		(1.238)
Nutrient retention ability of soil has moderate problem (=1 if yes)		-1.784*	-0.692	-1.059
		(0.992)	(0.691)	(1.022)
Rooting condition is not or a slight constraint (=1 if yes)		1.620***	1.635***	1.571**
		(0.606)	(0.608)	(0.635)
Rooting condition is a moderate constraint (=1 if yes)		0.023	0.026	0.048
		(0.424)	(0.424)	(0.442)
Oxygen availability to roots is not or a slight constraint (=1 if yes)		0.690	0.709	0.572
		(0.785)	(0.792)	(0.842)
Oxygen availability to roots is a moderate constraint (=1 if yes)		-0.266	-0.249	-0.316
		(0.589)	(0.593)	(0.603)
Soil toxicity is not or a slight constraint (=1 if yes)		-	-	-
Soil toxicity is a moderate constraint (=1 if yes)			1.101	
			(1.247)	
Workability of soil is not or a slight constraint (=1 if yes)		-2.051***	-2.076***	-1.978***
		(0.734)	(0.743)	(0.742)
Workability of soil is a moderate constraint (=1 if yes)		-0.696	-0.706	-0.615
		(0.607)	(0.609)	(0.614)
Central region (=1 if yes)			-0.560*	
			(0.334)	

South region (=1 if yes)					-0.461	
					(0.449)	
Tropical warm and semiarid agro-ecological zone (=1)						0.782
						(0.518)
Tropical warm and sub-humid agro-ecological zone (=1)						0.729
						(0.498)
Tropical cool and semiarid agro-ecological zone (=1)						0.101
						(0.772)
2016 year dummy (=1)	0.965***	1.045***	0.857***	0.804***	0.801***	0.804***
	(0.168)	(0.206)	(0.225)	(0.233)	(0.234)	(0.236)
Constant	5.227***	5.176***	3.361**	5.283	4.459	3.389
	(0.814)	(1.065)	(1.422)	(4.757)	(5.202)	(4.917)
Observations	1,048	1,048	1,042	1,042	1,042	1,042
R-squared	0.033	0.037	0.123	0.134	0.135	0.135

Note: Robust standard errors clustered at Enumeration Area level in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%; dependent variable, real price of fertilizer, and amount of land cultivated are transformed using inverse hyperbolic sine transformation. Fertilizer prices are adjusted to the average October to December 2015 national prices. The full regression results are presented in Table A2-2 in the Appendix.

Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-4: Demand for Commercial NPK and Urea Fertilizer among Voucher Non-recipients using Household Fixed Effects

Variables	**Dependent Variable: Arcsinh (kg of commercial fertilizer acquired per farm)**	
	NPK	Urea
Arcsinh (real price of fertilizer in Kw/kg)	-0.806***	-0.837***
	(0.235)	(0.169)
Wealth Index	0.049***	0.034**
	(0.017)	(0.016)
Arcsinh (Amount of land cultivated by HH in ha)	1.572***	1.532***
	(0.263)	(0.293)
Arcsinh (Amount of land cultivated by HH in ha) X Soil quality index	-0.122	0.048
	(0.151)	(0.154)
Number of working age (15 to 65) HH members	0.257	0.117
	(0.190)	(0.181)
Number of working age (15 to 65) HH members squared	-0.167	0.036
	(0.148)	(0.151)
Age of HH head	0.024	0.000
	(0.018)	(0.018)
Age of HH head square	0.032	0.034
	(0.142)	(0.198)
Log (annual precipitation in mm)	-0.021	-0.005
	(0.037)	(0.043)
Log (annual precipitation in mm) squared	0.000	0.000
	(0.000)	(0.000)
2016 year dummy	0.844***	1.002***
	(0.272)	(0.265)
Constant	-84.259	-101.923*
	(64.163)	(51.446)
Socio-econ variables	YES	YES
Fert Advise and distance to ag mkt	YES	YES
Environmental & soil quality variables	YES	YES
Agro-ecological dummies	YES	YES
Regional dummies	NO	NO
Number of observations	1,042	1,042
R-squared	0.141	0.139

Note: Robust standard errors clustered at Enumeration Level in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. The base group for the soil nutrient content and retention ability variables is "severe or very severe constraint."

Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-5: Descriptive Statistics on Consumer Surplus (in MK) from Redemption of Vouchers for 20 kg Fertilizer (with and without resell option) under FISP Based on Fertilizer Demand Estimates in Tables 7 and 8

Fertilizer resell regime	Mean	Median	20th percentile	80th percentile	Standard Deviation
Without resell option	6,886.5	6,340.6	3,704.5	10,405.5	3,740.2
With fertilizer resell at P_s	18,689.0	11,982.4	4,557.6	27,008.3	20,202.1
With fertilizer resell at P'_m	7,270.5	6,865.7	4,200.0	10,427.7	3,540.8

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-6: Aggregate Consumer Surplus (billions of MK), Program Cost (billions of MK), and Benefit-Cost Ratios from Redemption of Vouchers for 20 kg Fertilizer (with and without resell option) Based on Fertilizer Demand Estimates in Tables 7 and 8

Fertilizer resell regime	Consumer surplus	Cost of program	Benefit/Cost
Without resell option	37.68	61.81	0.61
With fertilizer resell at P_s	103.77	63.18	1.64
With fertilizer resell at P'_m	39.78	63.24	0.63

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-7: Number of Voucher Non-recipients in the Sample in Each Demand Category Using Fertilizer Demand Estimates in Table A2-4

Fertilizer Demand Scenarios	NPK	Urea
1: no demand at Ps	0	0
2: WTP for one bag < Ps < choke price <Pm	28	18
3: WTP for one bag < Ps <Pm < choke price	910	852
4: Ps < WTP for one bag <Pm	219	294
5: Pm < WTP for one bag (inframarginal)	66	59
Total	1223	1223

Note: P_m = farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer in 2016/17).
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-8: Amount of NPK and Urea (kg) Demanded by Voucher Non-recipients at the Subsidized Price Using Fertilizer Demand Estimates in Table A2-4

	NPK		urea	
Fertilizer demand scenarios	**Mean**	**Median**	**Mean**	**Median**
1: no demand at Ps	0.00	0.00	0.00	0.00
2: WTP for one bag < Ps < choke price <Pm	3.14	3.27	3.07	3.40
3: WTP for one bag < Ps <Pm < choke price	19.84	17.04	22.69	20.93
4: Ps < WTP for one bag <Pm	89.01	76.75	96.71	84.15
5: Pm < WTP for one bag (inframarginal)	345.60	306.63	325.76	290.20

Note: P_m = farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in the FISP for either type of fertilizer in 2016/17)
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-9: Number of Voucher Recipients in Each Demand Category After Matching Based on Fertilizer Demand Estimates in Table A2-4

Fertilizer Demand Scenarios	NPK	Urea
1: no demand at Ps	0	0
2: WTP for one bag < Ps < choke price <Pm	5	1
3: WTP for one bag < Ps <Pm < choke price	279	221
4: Ps < WTP for one bag <Pm	141	196
5: Pm < WTP for one bag (inframarginal)	49	56
Total	474	474

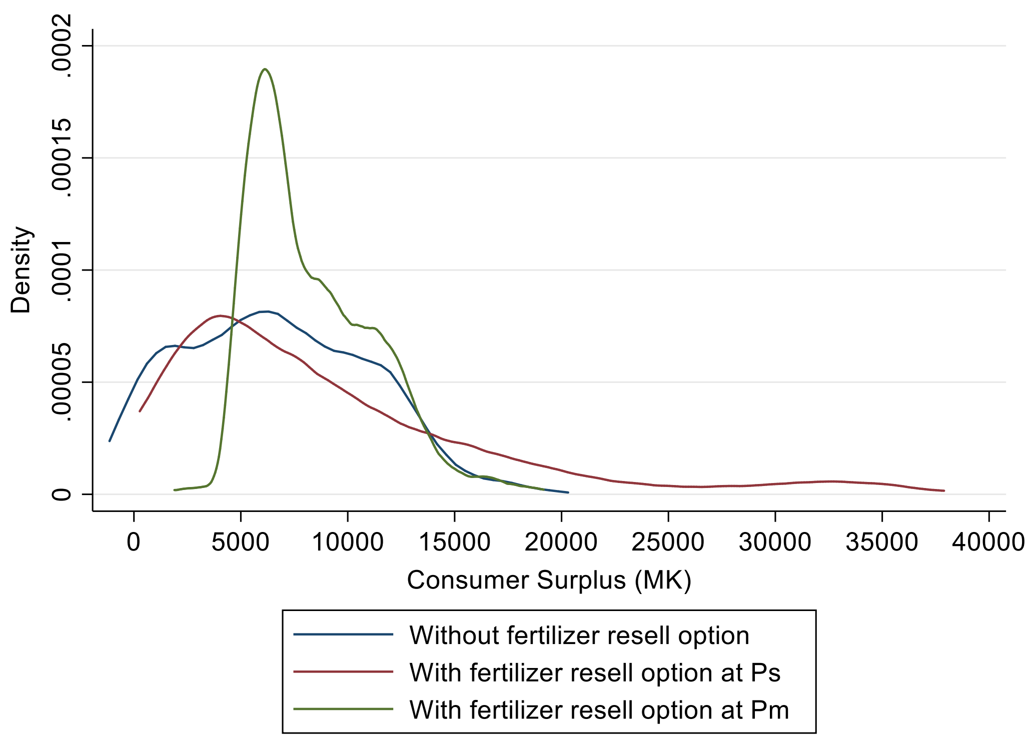
Note: P_m = farm-gate price of fertilizer; P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer).
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-10: Descriptive Statistics on Consumer Surplus (in MK) from Redemption of Vouchers for 50 kg Fertilizer (with and without resell option) under FISP Based on Fertilizer Demand Estimates in Table A2-4

Fertilizer resell regime	Mean	Median	20th percentile	80th percentile	Standard Deviation
Without resell option	11,053.0	10,385.6	3,247.1	17,811.0	7,835.8
With fertilizer resell at P_s	19,172.7	12,314.8	4,250.2	28,047.4	21,627.4
With fertilizer resell at P'_m	14,013.4	12,395.5	6,500.0	20,427.2	6,756.6

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Figure A2-1: Kernel Distribution of Consumer Surplus per Voucher for Different Fertilizer Resell Regimes Based on Fertilizer Demand Estimates in Table A2-4



Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-11: Aggregate Consumer Surplus (billions of MK), Program Cost (billions of MK), and Benefit-Cost Ratios for FISP Based on Fertilizer Demand Estimates in Table A2-4

Fertilizer resell regime	Consumer surplus	Cost of program	Benefit/Cost
Without resell option	61.06	141.49	0.43
With fertilizer resell at P_s	105.75	157.96	0.67
With fertilizer resell at P'_m	77.52	158.25	0.49

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Figure A2-2: Distribution of the Share of Redeemed Fertilizer Coupons and Aggregate Consumer Surplus Over Wealth Quartiles in 2016 Based on Fertilizer Demand Estimates in Table A2-4

Note: The wealth quartiles are calculated nationally after combining fertilizer voucher recipients and non-recipients. The 1st quartile includes households in the bottom 25% of the wealth index value. Similarly, households in the 2nd quartile (between 25% and 50%), 3rd quartile (between 50% and 75%), and 4th quartile (between 75% and 100%) in national wealth index value distribution.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-12: Descriptive Statistics on Consumer Surplus in MK from Redemption of Vouchers for either 50 kg or 20 kg Fertilizer Based on Fertilizer Demand Estimates in Table A2-4

	Without resell option		With fertilizer resell at P_s		With fertilizer resell at P'_m	
Statistics	**Value**	**% change from status quo**	**Value**	**% change from status quo**	**Value**	**% change from status quo**
Mean	11,540.4	4.4	19,172.7	0.0	14,031.2	0.1
Median	10896.31	4.9	12314.75	0.0	12395.49	0.0
20th percentile	4035.7	24.3	4250.2	0.0	6500.0	0.0
80th percentile	18546.0	4.1	28047.4	0.0	20427.2	0.0

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-13: Aggregate Consumer Surplus (billions of MK), Program Cost (billions of MK), and Benefit-Cost Ratios for FISP Beneficiaries from Redeeming Vouchers for either 20 kg or 50 kg bag Fertilizer Based on Fertilizer Demand Estimates in Table A2-4

Fertilizer resell regime	Consumer surplus	Cost of program	Benefit/Cost
Without resell option	63.81	123.16	0.52
With fertilizer resell at P_s	105.75	64.26	1.65
With fertilizer resell at P'_m	77.61	157.38	0.49

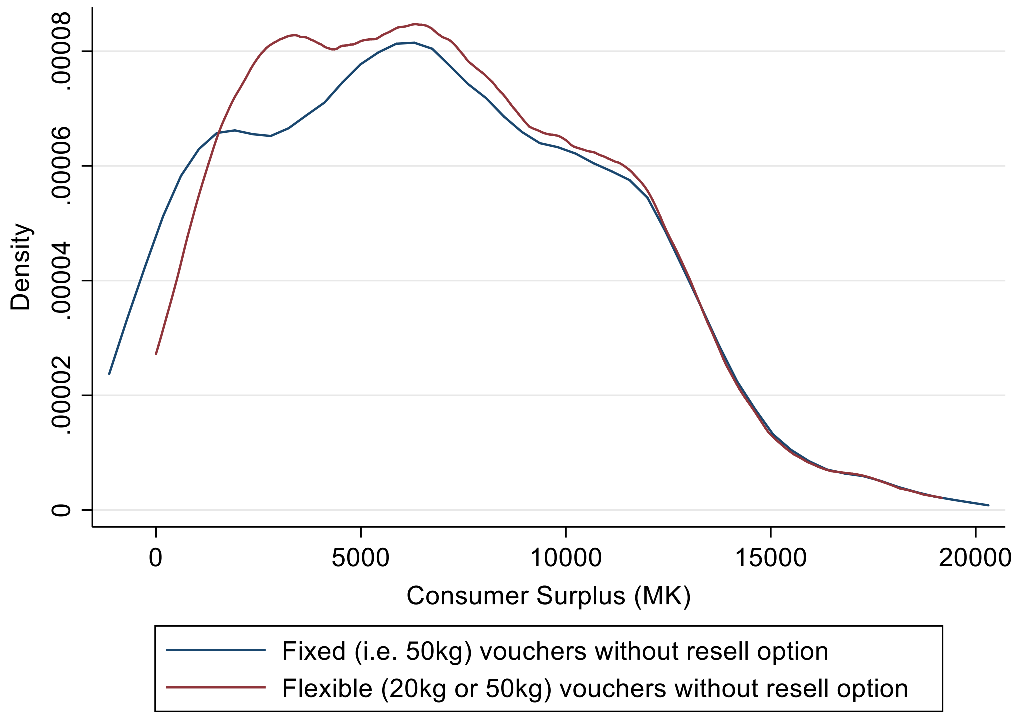
Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-14: Descriptive Statistics on Consumer Surplus in MK from Redemption of Vouchers for 20 kg Bag Fertilizer Based on Fertilizer Demand Estimates in Table A2-4

	Without resell option		With fertilizer resell at P_s		With fertilizer resell at P'_m	
Statistics	**Value**	**% change from status quo**	**Value**	**% change from status quo**	**Value**	**% change from status quo**
Mean	6,939.7	-37.2	19,172.7	0.0	7,306.6	-47.9
Median	6424.43	-38.1	12314.75	0	6865.47	-44.6
20th percentile	3600.0	10.9	4250.2	0.0	4131.2	-36.4
80th percentile	10500.0	-41.0	28047.4	0.0	10569.6	-48.3

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Figure A2-3: Kernel Distribution of Consumer Surplus per Voucher for Fixed Redemption (i.e. 50 kg bags) versus Flexible Redemption (20 kg or 50 kg bags) of FISP Vouchers without Fertilizer Resell Option Based on Fertilizer Demand Estimates in Table A2-4



Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Table A2-15: Aggregate Consumer Surplus (billions of MK), Program Cost (billions of MK), and Benefit-Cost Ratios for FISP Beneficiaries from Redeeming Vouchers for 20 kg Bag Fertilizer Based on Fertilizer Demand Estimates in Table A2-4

Fertilizer resell regime	Consumer surplus	Cost of program	Benefit/Cost
Without resell option	38.37	61.93	0.62
With fertilizer resell at P_s	105.75	63.18	1.67
With fertilizer resell at P'_m	40.40	63.24	0.64

Note: P_s = subsidized price of fertilizer (70 MK/kg in FISP for either type of fertilizer); P'_m = the median resell price of fertilizer estimated at 177.1 MK/kg.
Source: Author's analysis from IHPS data for Malawi collected in 2013 and 2016/17.

Chapter 3 Appendix

Table A3-1: OLS estimates for determinants of real annual expenditure with all observations

Variables	Dependent Variable: Arcsinh (Real annual consumption per capita in 2016 prices)		
	1	**2**	**3**
Arcsinh (Number of crops grown)	0.010		
	(0.014)		
Arcsinh (Simpson's index measure of crop diversity)		−0.051**	
		(0.025)	
HH grows two or more crops (=1 if yes)			-0.036**
			(0.014)
HH experienced loss due to drought or flooding (=1 if yes)	−0.051***	−0.047***	−0.046***
	(0.009)	(0.009)	(0.009)
HH experienced loss due to crop disease or pest (=1 if yes)	0.082***	0.088***	0.087***
	(0.015)	(0.015)	(0.015)
Arcsinh (size of cultivated land by HH in acre)	0.205***	0.213***	0.214***
	(0.011)	(0.011)	(0.010)
HH size	−0.100***	−0.100***	−0.100***
	(0.003)	(0.003)	(0.003)
Female headed HH (=1 if yes)	−0.030***	−0.030***	−0.030***
	(0.010)	(0.010)	(0.010)
Age of HH head	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)
Years of education for HH head	0.041***	0.041***	0.041***
	(0.002)	(0.002)	(0.002)
HH head engaged in nonagricultural enterprise (=1 if yes)	0.218***	0.217***	0.217***
	(0.013)	(0.013)	(0.013)
Fertilizer application intensity (kg/acre)	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
2010 year dummy (=1 if yes)	−0.109***	−0.114***	-0.114***
	(0.020)	(0.020)	(0.020)

2016 year dummy (=1 if yes)	−0.122***	−0.126***	-0.123***
	(0.019)	(0.019)	(0.018)
Constant	12.064***	12.095***	12.102***
	(0.046)	(0.043)	(0.043)
District dummies	Yes	Yes	Yes
Observations	29,078	29,078	29,078
R-squared	0.354	0.354	0.355

Source: Authors' calculation based on IHS2–4.
Note: HH = Household; *, **, and *** show the coefficient is significant at 10 percent, 5 percent, and 1 percent significance levels respectively. The standard errors are robust and clustered at the enumeration area level. Arcsinh refers to the inverse hyperbolic sine transformation. It is similar to the log transformation but allows for zero and even negative values. The box with missing values means the corresponding explanatory variable has not been included in the regression.

Table A3-2: OLS estimates for determinants of real annual expenditure among farm households in the lowest four consumption quintiles

Variables	Dependent Variable: Arcsinh (Real annual consumption per capita in 2016 prices)		
	1	2	3
Arcsinh (Number of crops grown)	0.062***		
	(0.011)		
Arcsinh (Simpson's index measure of crop diversity)		0.058***	
		(0.020)	
HH grows two or more crops (=1 if yes)			0.015
			(0.011)
HH experienced loss due to drought or flooding (=1 if yes)	−0.022**	−0.019**	−0.017**
	(0.009)	(0.009)	(0.009)
HH experienced loss due to crop disease or pest (=1 if yes)	0.078***	0.085***	0.087***
	(0.013)	(0.013)	(0.013)
Arcsinh (size of cultivated land by HH in acre)	0.138***	0.147***	0.152***
	(0.010)	(0.009)	(0.009)
HH size	−0.073***	−0.073***	−0.073***
	(0.002)	(0.002)	(0.002)
Female-headed HH (=1 if yes)	−0.034***	−0.034***	−0.034***
	(0.009)	(0.009)	(0.009)
Age of HH head	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Years of education for HH head	0.023***	0.023***	0.023***
	(0.001)	(0.001)	(0.001)
HH head engaged in non-agricultural enterprise (=1 if yes)	0.134***	0.134***	0.134***
	(0.011)	(0.011)	(0.011)
Fertilizer application intensity (kg/acre)	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
2010 year dummy (=1 if yes)	−0.040**	−0.051***	−0.054***
	(0.016)	(0.016)	(0.016)
2016 year dummy (=1 if yes)	−0.019	−0.026*	−0.029*

	(0.015)	(0.015)	(0.015)
Constant	12.014***	12.084***	12.092***
	(0.036)	(0.033)	(0.033)
District dummies	Yes	Yes	Yes
Observations	23,216	23,216	23,216
R-squared	0.244	0.242	0.241

Source: Authors' calculation based on IHS 2–4.
Note: HH = Household; *, **, and *** show the coefficient is significant at 10 percent, 5 percent, and 1 percent significance levels respectively. The standard errors are robust and clustered at the enumeration area level. Arcsinh refers to the inverse hyperbolic sine transformation. It is similar to the log transformation but allows for zero and even negative values. The box with missing values means the corresponding explanatory variable has not been included in the regression.

Table A3-3: Marginal ordered logit estimates for determinants of poverty with all observations

Variables	Value of dependent variable	1	2	3
Arcsinh (Number of crops grown)	Ultra-poor (=1 if yes)	−0.029***		
		(0.008)		
	Moderate poor (=1 if yes)	−0.008***		
		(0.002)		
	Not poor (=1 if yes)	0.037***		
		(0.010)		
Arcsinh (Simpson's index measure of crop diversity)	Ultra-poor (=1 if yes)		−0.017	
			(0.014)	
	Moderate poor (=1 if yes)		−0.004	
			(0.004)	
	Not poor (=1 if yes)		0.021	
			(0.017)	
HH grows two or more crops (=1 if yes)	Ultra-poor (=1 if yes)			0.004
				(0.007)
	Moderate poor (=1 if yes)			0.001
				(0.002)
	Not poor (=1 if yes)			−0.005
				(0.009)
HH experienced loss due to drought or flooding (=1 if yes)	Ultra-poor (=1 if yes)	0.019***	0.017***	0.016***
		(0.006)	(0.006)	(0.006)
	Moderate poor (=1 if yes)	0.005***	0.004***	0.004***
		(0.002)	(0.002)	(0.002)
	Not poor (=1 if yes)	−0.024***	−0.021***	−0.020***
		(0.007)	(0.007)	(0.007)
HH experienced loss due to crop disease or pest (=1 if yes)	Ultra-poor (=1 if yes)	−0.052***	−0.056***	−0.057***
		(0.009)	(0.009)	(0.009)
	Moderate poor (=1 if yes)	−0.013***	−0.014***	−0.015***
		(0.003)	(0.003)	(0.003)
	Not poor (=1 if yes)	0.065***	0.070***	0.072***

Variables	Value of dependent variable	1	2	3
		(0.012)	(0.012)	(0.012)
Arcsinh (size of cultivated land by HH in acre)	Ultra-poor (=1 if yes)	−0.106***	−0.112***	−0.114***
		(0.007)	(0.006)	(0.006)
	Moderate poor (=1 if yes)	−0.028***	−0.029***	−0.030***
		(0.002)	(0.002)	(0.002)
	Not poor (=1 if yes)	0.134***	0.141***	0.144***
		(0.008)	(0.008)	(0.008)
HH size	Ultra-poor (=1 if yes)	0.056***	0.056***	0.056***
		(0.002)	(0.002)	(0.002)
	Moderate poor (=1 if yes)	0.014***	0.014***	0.014***
		(0.001)	(0.001)	(0.001)
	Not poor (=1 if yes)	−0.070***	−0.070***	−0.070***
		(0.002)	(0.002)	(0.002)
Female-headed HH (=1 if yes)	Ultra-poor (=1 if yes)	0.021***	0.021***	0.020***
		(0.006)	(0.006)	(0.006)
	Moderate poor (=1 if yes)	0.005***	0.005***	0.005***
		(0.002)	(0.002)	(0.002)
	Not poor (=1 if yes)	−0.026***	−0.026***	−0.026***
		(0.007)	(0.007)	(0.007)
Age of HH head	Ultra-poor (=1 if yes)	−0.001***	−0.001***	−0.001***
		(0.000)	(0.000)	(0.000)
	Moderate poor (=1 if yes)	−0.000***	−0.000***	−0.000***
		(0.000)	(0.000)	(0.000)
	Not poor (=1 if yes)	0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
Years of education for HH head	Ultra-poor (=1 if yes)	−0.018***	−0.018***	−0.018***
		(0.001)	(0.001)	(0.001)
	Moderate poor (=1 if yes)	−0.005***	-0.005***	−0.005***
		(0.000)	(0.000)	(0.000)
	Not poor (=1 if yes)	0.023***	0.023***	0.023***
		(0.001)	(0.001)	(0.001)

Variables	Value of dependent variable	1	2	3
HH head engaged in non-agricultural enterprise (=1 if yes)	Ultra-poor (=1 if yes)	−0.113***	−0.113***	−0.113***
		(0.008)	(0.008)	(0.008)
	Moderate poor (=1 if yes)	−0.029***	−0.029***	-0.029***
		(0.003)	(0.003)	(0.003)
	Not poor (=1 if yes)	0.142***	0.142***	0.142***
		(0.010)	(0.010)	(0.010)
Fertilizer application intensity (kg/acre)	Ultra-poor (=1 if yes)	−0.002***	−0.002***	−0.002***
		(0.000)	(0.000)	(0.000)
	Moderate poor (=1 if yes)	−0.000***	−0.000***	−0.000***
		(0.000)	(0.000)	(0.000)
	Not poor (=1 if yes)	0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
2010 year dummy (=1 if yes)	Ultra-poor (=1 if yes)	0.038***	0.000	0.044***
		(0.011)	(0.000)	(0.011)
	Moderate poor (=1 if yes)	0.011***	0.000	0.013***
		(0.003)	(0.000)	(0.003)
	Not poor (=1 if yes)	−0.048***	0.000	−0.057***
		(0.015)	(0.000)	(0.014)
2016 year dummy (=1 if yes)	Ultra-poor (=1 if yes)	0.032***	0.043***	0.036***
		(0.011)	(0.011)	(0.011)
	Moderate poor (=1 if yes)	0.009***	0.012***	0.011***
		(0.003)	(0.003)	(0.003)
	Not poor (=1 if yes)	−0.041***	−0.055***	−0.047***
		(0.014)	(0.014)	(0.014)
District dummies		Yes	Yes	Yes

Source: Authors' calculation based on IHS 2–4.

Note: HH = Household; *, **, and *** show the coefficient is significant at 10 percent, 5 percent, and 1 percent significance levels respectively. The standard errors are clustered at the enumeration area level. Arcsinh refers to the inverse hyperbolic sine transformation. It is similar to the log transformation but allows for zero and even negative values. The box with missing values means the corresponding explanatory variable has not been included in the regression.

Table A3-4: Marginal ordered logit estimates for determinants of poverty among farm households in the lowest four consumption quintiles

Variables	Value of dependent variable	1	2	3
Arcsinh (Number of crops grown)	Ultra-poor (=1 if yes)	−0.047***		
		(0.009)		
	Moderate poor (=1 if yes)	−0.003***		
		(0.001)		
	Not poor (=1 if yes)	0.051***		
		(0.010)		
Arcsinh (Simpson's index measure of crop diversity)	Ultra-poor (=1 if yes)		−0.046***	
			(0.016)	
	Moderate poor (=1 if yes)		−0.003**	
			(0.001)	
	Not poor (=1 if yes)		0.049***	
			(0.017)	
HH grows two or more crops (=1 if yes)	Ultra-poor (=1 if yes)			−0.007
				(0.009)
	Moderate poor (=1 if yes)			−0.000
				(0.001)
	Not poor (=1 if yes)			0.007
				(0.009)
HH experienced loss due to drought or flooding (=1 if yes)	Ultra-poor (=1 if yes)	0.013*	0.011	0.009
		(0.007)	(0.007)	(0.007)
	Moderate poor (=1 if yes)	0.001*	0.001	0.001
		(0.001)	(0.001)	(0.001)
	Not poor (=1 if yes)	−0.014*	−0.012	−0.010
		(0.008)	(0.008)	(0.008)
HH experienced loss due to crop disease or pest (=1 if yes)	Ultra-poor (=1 if yes)	−0.063***	−0.067***	−0.070***
		(0.011)	(0.011)	(0.011)
	Moderate poor (=1 if yes)	−0.004***	−0.005***	−0.005***
		(0.001)	(0.001)	(0.001)

Variables	Value of dependent variable	1	2	3
	Not poor (=1 if yes)	0.067***	0.072***	0.075***
		(0.012)	(0.012)	(0.012)
Arcsinh (size of cultivated land by HH in acre)	Ultra-poor (=1 if yes)	−0.109***	−0.116***	−0.120***
		(0.008)	(0.008)	(0.007)
	Moderate poor (=1 if yes)	−0.008***	−0.008***	−0.009***
		(0.002)	(0.002)	(0.002)
	Not poor (=1 if yes)	0.117***	0.124***	0.129***
		(0.008)	(0.008)	(0.008)
HH size	Ultra-poor (=1 if yes)	0.058***	0.058***	0.058***
		(0.002)	(0.002)	(0.002)
	Moderate poor (=1 if yes)	0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)
	Not poor (=1 if yes)	−0.062***	−0.062***	−0.062***
		(0.002)	(0.002)	(0.002)
Female headed HH (=1 if yes)	Ultra-poor (=1 if yes)	0.023***	0.023***	0.022***
		(0.007)	(0.007)	(0.007)
	Moderate poor (=1 if yes)	0.002***	0.002***	0.002**
		(0.001)	(0.001)	(0.001)
	Not poor (=1 if yes)	−0.024***	−0.024***	−0.024***
		(0.008)	(0.008)	(0.008)
Age of HH head	Ultra-poor (=1 if yes)	−0.001***	−0.001***	−0.001***
		(0.000)	(0.000)	(0.000)
	Moderate poor (=1 if yes)	−0.000***	−0.000***	−0.000***
		(0.000)	(0.000)	(0.000)
	Not poor (=1 if yes)	0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
Years of education for HH head	Ultra-poor (=1 if yes)	−0.017***	−0.017***	−0.017***
		(0.001)	(0.001)	(0.001)
	Moderate poor (=1 if yes)	−0.001***	−0.001***	−0.001***
		(0.000)	(0.000)	(0.000)

Variables	Value of dependent variable	1	2	3
	Not poor (=1 if yes)	0.018***	0.018***	0.018***
		(0.001)	(0.001)	(0.001)
HH head engaged in non-agricultural enterprise (=1 if yes)	Ultra-poor (=1 if yes)	−0.106***	−0.107***	−0.107***
		(0.009)	(0.009)	(0.009)
	Moderate poor (=1 if yes)	−0.008***	−0.008***	−0.008***
		(0.002)	(0.002)	(0.002)
	Not poor (=1 if yes)	0.114***	0.114***	0.114***
		(0.010)	(0.010)	(0.010)
Fertilizer application intensity (kg/acre)	Ultra-poor (=1 if yes)	−0.002***	−0.002***	−0.002***
		(0.000)	(0.000)	(0.000)
	Moderate poor (=1 if yes)	−0.000***	−0.000***	−0.000***
		(0.000)	(0.000)	(0.000)
	Not poor (=1 if yes)	0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
2010 year dummy (=1 if yes)	Ultra-poor (=1 if yes)	0.000	0.028**	0.031**
		(0.000)	(0.013)	(0.013)
	Moderate poor (=1 if yes)	0.000	0.002*	0.002*
		(0.000)	(0.001)	(0.001)
	Not poor (=1 if yes)	0.000	−0.030**	−0.033**
		(0.000)	(0.014)	(0.014)
2016 year dummy (=1 if yes)	Ultra-poor (=1 if yes)	0.020	0.014	0.016
		(0.013)	(0.013)	(0.013)
	Moderate poor (=1 if yes)	0.001	0.001	0.002
		(0.001)	(0.001)	(0.001)
	Not poor (=1 if yes)	−0.022	−0.015	−0.018
		(0.014)	(0.014)	(0.014)
District dummies		Yes	Yes	Yes

Source: Authors' calculation based on IHS 2−4.
Note: HH = Household; *, **, and *** show the coefficient is significant at 10 percent, 5 percent, and 1 percent significance levels respectively. The standard errors are clustered at the enumeration area level. Arcsinh is like a log transformation. Arcsinh refers to the inverse hyperbolic sine transformation. It is similar

to the log transformation but allows for zero and even negative values. The box with missing values means the corresponding explanatory variable has not been included in the regression.

Table A3-5: OLS estimates for determinants of crop diversity (number of crops grown) with all observations

Variables	Dependent Variable: Arcsinh (Number of Crops Grown)		
	1	2	3
HH experienced loss due to crop shock (=1 if yes)	0.125***		
	(0.009)		
HH experienced loss due to drought or flooding (=1 if yes)		0.113***	
		(0.009)	
HH experienced loss due to crop disease or pest (=1 if yes)			0.191***
			(0.015)
Arcsinh (size of cultivated land by HH in acre)	0.260***	0.261***	0.261***
	(0.008)	(0.008)	(0.008)
HH size	−0.002	−0.002	−0.003
	(0.002)	(0.002)	(0.002)
Female-headed HH (=1 if yes)	−0.000	−0.000	−0.002
	(0.008)	(0.008)	(0.008)
Age of HH head	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
Years of education for HH head	−0.002*	−0.002*	−0.002**
	(0.001)	(0.001)	(0.001)
HH head engaged in nonagricultural enterprise (=1 if yes)	−0.005	−0.004	−0.009
	(0.010)	(0.010)	(0.010)
Fertilizer application intensity (kg/acre)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
2010 year dummy (=1 if yes)	−0.247***	−0.251***	−0.236***
	(0.015)	(0.015)	(0.016)
2016 year dummy (=1 if yes)	−0.175***	−0.178***	−0.139***
	(0.017)	(0.017)	(0.017)
Constant	1.457***	1.469***	1.512***
	(0.031)	(0.030)	(0.032)
District dummies	Yes	Yes	Yes

Observations	29,078	29,078	29,078
R-squared	0.309	0.307	0.308

Source: Authors' calculation based on IHS 2–4.
Note: HH = Household; *, **, and *** show the coefficient is significant at 10 percent, 5 percent, and 1 percent significance levels respectively. The standard errors are robust and clustered at the enumeration area level. Arcsinh refers to the inverse hyperbolic sine transformation. It is similar to the log transformation but allows for zero and even negative values. The box with missing values means the corresponding explanatory variable has not been included in the regression.

Table A3-6: OLS estimates for determinants of crop diversity (Simpson's Index) with all observations

	Dependent Variable: Arcsinh (Simpson Diversification Index (SDI))		
Variables	**1**	**2**	**3**
HH experienced loss due to crop shock (=1 if yes)	0.063***		
	(0.005)		
HH experienced loss due to drought or flooding (=1 if yes)		0.058***	
		(0.005)	
HH experienced loss due to crop disease or pest (=1 if yes)			0.078***
			(0.007)
Arcsinh (size of cultivated land by HH in acre)	0.121***	0.121***	0.121***
	(0.004)	(0.004)	(0.004)
HH size	−0.003***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)
Female headed HH (=1 if yes)	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)
Age of HH head	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)
Years of education for HH head	−0.001**	−0.001**	−0.002***
	(0.001)	(0.001)	(0.001)
HH head engaged in non-agricultural enterprise (=1 if yes)	−0.004	−0.003	−0.005
	(0.005)	(0.005)	(0.005)
Fertilizer application intensity (kg/acre)	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
2010 year dummy (=1 if yes)	−0.067***	−0.069***	−0.066***
	(0.007)	(0.007)	(0.007)
2016 year dummy (=1 if yes)	−0.056***	−0.058***	−0.042***
	(0.008)	(0.008)	(0.008)
Constant	0.329***	0.334***	0.360***
	(0.016)	(0.016)	(0.016)
Observations	29,078	29,078	29,078

R-squared	0.237	0.235	0.232

Source: Authors' calculation based on IHS 2–4.
Note: HH = Household; *, **, and *** show the coefficient is significant at 10 percent, 5 percent, and 1 percent significance levels respectively. The standard errors are robust and clustered at the enumeration area level. arcsinh refers to the inverse hyperbolic sine transformation. It is similar to the log transformation but allows for zero and even negative values. The box with missing values means the corresponding explanatory variable has not been included in the regression.

Chapter 4 Appendix

Table 4-1A: IR estimates for maize yield per ha: District fixed effects

	Small (<10 ha)		Medium (10 - 50 ha)		Large (>50 ha)	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.172***	0.171***	-0.536	-0.598	-0.009	-0.050
	(0.028)	(0.027)	(0.414)	(0.402)	(0.069)	(0.069)
Ln(crop area in ha)	-0.379***	-0.384***	0.132	0.163	-0.135	-0.111
	(0.022)	(0.023)	(0.115)	(0.155)	(0.082)	(0.084)
Arcsinh(chemical fertilizer use in quintals per ha)	0.253***	0.212***	2.268***	2.112***	28.123**	22.829**
	(0.044)	(0.044)	(0.313)	(0.514)	(11.462)	(11.249)
Arcsinh(No. of workers per ha)	0.193***	0.192***	0.174	0.150	0.016	0.012
	(0.037)	(0.035)	(0.118)	(0.148)	(0.061)	(0.064)
Used pesticides		-0.056		0.199		0.161
		(0.116)		(0.505)		(0.167)
Used fungicides		-0.403*		-		0.240
		(0.225)				(0.200)
Used herbicides		0.149		0.021		0.043
		(0.096)		(1.078)		(0.116)
Used improved seeds		0.180**		-0.120		0.333*
		(0.072)		(0.567)		(0.199)
Experienced crop shocks		-0.270***		-0.297		-0.300**
		(0.048)		(0.332)		(0.127)
Year=2014[a]	0.065	0.017	0.428	0.362	-0.305	-0.229
	(0.059)	(0.056)	(0.501)	(0.612)	(0.225)	(0.220)
Constant	1.097***	1.203***	4.103***	4.555***	3.862***	3.893***
	(0.112)	(0.108)	(1.292)	(1.452)	(0.469)	(0.384)
Number of observations	2,961	2,961	119	118	414	404
R2	0.208	0.230	0.284	0.299	0.093	0.127

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.
Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

Table 4-2A: IR estimates for wheat yield per ha: District fixed effects

	Small (<10 ha)		Medium (10 - 50 ha)		Large (>50 ha)	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.128**	0.121**	0.580	0.503	0.919***	0.782**
	(0.057)	(0.056)	(0.589)	(0.768)	(0.336)	(0.341)
Ln(crop area in ha)	-0.236***	-0.251***	0.209	0.318	-0.619**	-0.560**
	(0.045)	(0.043)	(0.368)	(0.518)	(0.265)	(0.264)
Arcsinh(chemical fertilizer use in quintals per ha)	0.212***	0.187***	1.206*	1.334*	41.203	54.179
	(0.046)	(0.046)	(0.656)	(0.792)	(41.847)	(46.138)
Arcsinh(No. of workers per ha)	0.091**	0.081**	0.788***	0.905***	0.457***	0.333**
	(0.040)	(0.039)	(0.227)	(0.278)	(0.145)	(0.144)
Used pesticides		0.059		-0.044		0.714
		(0.115)		(0.619)		(0.451)
Used fungicides		0.220		-0.253		0.120
		(0.136)		(0.233)		(0.239)
Used herbicides		0.137**		0.409		-1.381***
		(0.060)		(0.293)		(0.384)
Used improved seeds		0.202***		0.277		-0.610***
		(0.068)		(0.477)		(0.165)
Experienced crop shocks		-0.229***		-0.205		-0.358
		(0.064)		(0.559)		(0.258)
Year=2014[a]	0.093	0.043	0.780	0.630	0.484	0.405
	(0.057)	(0.056)	(0.667)	(0.561)	(0.432)	(0.443)
Constant	1.500***	1.541***	-0.621	-0.831	-0.214	1.859*
	(0.133)	(0.134)	(1.037)	(1.214)	(1.360)	(1.064)
Number of observations	1,523	1,523	39	39	154	150
R2	0.106	0.134	0.670	0.699	0.236	0.328

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.

Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.

a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

Table 4-3A: IR estimates for teff yield per ha: District fixed effects

	Small (<10 ha)		Medium (10 - 50 ha)		Large (>50 ha)	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.245***	0.242***	0.981*	0.983*	-0.116	-0.057
	(0.045)	(0.046)	(0.554)	(0.559)	(0.197)	(0.172)
Ln(crop area in ha)	-0.393***	-0.393***	-0.627***	-0.555**	-0.328**	-0.232
	(0.034)	(0.035)	(0.225)	(0.232)	(0.146)	(0.160)
Arcsinh(chemical fertilizer use in quintals per ha)	0.211***	0.206***	-1.386	-2.278***	-20.332*	-3.570
	(0.041)	(0.041)	(0.928)	(0.802)	(10.907)	(17.680)
Arcsinh(No. of workers per ha)	0.220***	0.213***	0.183	0.122	-0.023	-0.079
	(0.033)	(0.033)	(0.188)	(0.188)	(0.054)	(0.085)
Used pesticides		0.046		0.749		-0.640
		(0.110)		(0.472)		(0.741)
Used fungicides		0.033		-		0.096
		(0.122)				(0.573)
Used herbicides		0.089		0.518		-0.331
		(0.055)		(0.424)		(0.373)
Used improved seeds		-0.014		-0.023		0.040
		(0.085)		(0.493)		(0.253)
Experienced crop shocks		-0.135**		-1.019**		0.078
		(0.057)		(0.477)		(0.300)
Year=2014[a]	0.212***	0.175***	0.393	0.900	-1.078***	-1.104***
	(0.053)	(0.051)	(0.793)	(0.678)	(0.315)	(0.347)
Constant	0.406***	0.461***	-0.690	-0.565	3.936***	3.554***
	(0.113)	(0.116)	(2.188)	(2.009)	(1.331)	(1.194)
Number of observations	2,201	2,201	66	65	121	110
R2	0.201	0.208	0.477	0.550	0.233	0.258

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.
Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

Table 4-4A: IR estimates for sorghum yield per ha: District fixed effects

	Small (<10 ha)		Medium (10 - 50 ha)		Large (>50 ha)	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.247***	0.242***	0.380***	0.386***	0.211***	0.199***
	(0.049)	(0.050)	(0.068)	(0.048)	(0.034)	(0.035)
Ln(crop area in ha)	-0.422***	-0.417***	-0.135***	-0.101***	-0.209***	-0.183***
	(0.043)	(0.043)	(0.030)	(0.029)	(0.024)	(0.023)
Arcsinh(chemical fertilizer use in quintals per ha)	-0.025	-0.022	-0.432	-1.032**	-4.514***	-4.175***
	(0.075)	(0.075)	(0.381)	(0.443)	(0.422)	(0.453)
Arcsinh(No. of workers per ha)	0.219***	0.214***	0.114***	0.101***	0.028	0.039
	(0.046)	(0.047)	(0.013)	(0.015)	(0.030)	(0.024)
Used pesticides		0.034		0.190		-0.344**
		(0.221)		(0.264)		(0.134)
Used fungicides		0.032		-		0.242***
		(0.135)				(0.048)
Used herbicides		0.013		-0.071*		0.013
		(0.118)		(0.041)		(0.061)
Used improved seeds		-0.194		-0.207		0.173**
		(0.232)		(0.268)		(0.078)
Experienced crop shocks		-0.150**		-0.572***		-0.495***
		(0.061)		(0.143)		(0.085)
Year=2014[a]	0.223***	0.184***	0.213***	0.166***	0.264***	0.227**
	(0.070)	(0.068)	(0.051)	(0.046)	(0.091)	(0.108)
Constant	0.927***	1.032***	1.689***	2.160***	2.529***	2.875***
	(0.135)	(0.145)	(0.201)	(0.222)	(0.163)	(0.150)
Number of observations	1,818	1,818	398	392	1,115	1,084
R2	0.187	0.193	0.050	0.130	0.096	0.164

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.
Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.

Table 4-5A: IR estimates for sesame yield per ha: District fixed effects

	Small (<10 ha)		Medium (10 - 50 ha)		Large (>50 ha)	
	m1	**m2**	**m3**	**m4**	**m5**	**m6**
Ln(holding size in ha)	0.349***	0.356***	-0.213**	-0.190**	0.146**	0.150**
	(0.120)	(0.120)	(0.095)	(0.085)	(0.069)	(0.070)
Ln(crop area in ha)	-0.396***	-0.382***	-0.107**	-0.096*	-0.039	-0.065
	(0.073)	(0.074)	(0.048)	(0.049)	(0.041)	(0.040)
Arcsinh(chemical fertilizer use in quintals per ha)	0.175	0.149	-0.439	-0.116	-0.526	-0.706*
	(0.245)	(0.210)	(0.504)	(0.528)	(0.561)	(0.411)
Arcsinh(No. of workers per ha)	0.236***	0.246***	0.021	0.034	-0.029	-0.030
	(0.073)	(0.073)	(0.028)	(0.028)	(0.026)	(0.025)
Used pesticides		-0.679*		0.095		0.358***
		(0.408)		(0.143)		(0.125)
Used fungicides		-		-0.041		0.201
				(0.087)		(0.219)
Used herbicides		-0.249*		-0.043		0.400***
		(0.149)		(0.326)		(0.107)
Used improved seeds		0.551		0.200**		-0.072
		(0.419)		(0.100)		(0.071)
Experienced crop shocks		-0.357***		-0.551***		-0.307**
		(0.090)		(0.156)		(0.146)
Year=2014[a]	-0.051	-0.053	1.410***	1.410***	1.266***	1.255***
	(0.139)	(0.124)	(0.207)	(0.190)	(0.348)	(0.312)
Constant	0.102	0.261	1.904***	2.245***	0.471	0.777*
	(0.299)	(0.290)	(0.407)	(0.335)	(0.350)	(0.406)
Number of observations	353	353	472	461	1,348	1,322
R2	0.141	0.183	0.512	0.541	0.386	0.412

Source: Authors' calculation from the 2014 and 2016 LSMS-ISA survey and 2014 and 2015 medium and large commercial farm survey.
Note: Dependent variable: Ln(yield) in quintals per ha. Robust standard errors adjusted for clustering at the Kebele level in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Inverse hyperbolic sine transformation used on chemical fertilizer per ha and no. workers per ha: $\log(y+(y^2+1)^{1/2})$.
a: the base-year for small-scale farming is 2016 while for medium and large-scale farming it is 2015.