FACTOR MARKETS, RELATIVE PRICES, AND INPUT USE IN EASTERN AND SOUTHERN AFRICA

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ABSTRACT

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Despite decades of targeted research and policy, agricultural input use in sub-Saharan Africa (SSA) remains low. Moreover, while it is increasingly understood that incomplete markets impose additional constraints on rural households, the role of factor market imperfections in limiting input use is under-studied. This dissertation, titled *Factor Markets, Relative Prices, and Input Use in Eastern and Southern Africa*, begins to fill this gap by exploring the link between agricultural factor markets, input use, and production in Eastern and Southern Africa, where land pressures and variability in production are particularly acute.

The first chapter uses three waves of the World Bank's Ethiopia Socioeconomic Survey to formally test whether imperfections in multiple markets affect fertilizer demand among smallholder famers in Ethiopia. The share of working-aged males in the household has a positive and fairly substantial effect on farm labor and conditional fertilizer demand, indicating that households are not participating fully in at least two factor markets and that labor-constrained households use less of either input. Consistent with there being frictions in local labor markets, farm labor demand is relatively inelastic with respect to the market wage. Moreover, fertilizer demand is relatively inelastic with respect to fertilizer prices among households with no migrant members, suggesting that policies which focus solely on lowering fertilizer prices are unlikely to greatly increase fertilizer use among certain types of households.

The second chapter extends this price elasticity analysis and draws on a 13-year panel dataset collected by Egerton University and Michigan State University to examine how Kenyan smallholders adjust demand for cultivated area and fertilizer in response to changing land, labor, and fertilizer prices. For both inputs, demand is relatively inelastic with respect to land rental rates and the local agricultural wage, though fertilizer demand increases as fertilizer prices decrease. This is counter to the hypothesis of complete markets, which implies that farm input demand depends on only relative prices and marginal products, and suggests the presence of transactions costs or other market frictions that prevent households from responding flexibly to changes in land and labor prices.

The third chapter uses two waves of a plot-level panel dataset of farmers' self-identified most and least fertile maize plots in Central Malawi to characterize the range in expected profitability of fertilizer and weeding labor use that is found within households and villages. Even with the plot fixed effects, there persist differences in returns to fertilizer and weeding labor between the most and least fertile plots in the sample, differences which translate into heterogeneity in expected profitability of use of either input. The greatest source of heterogeneity, however, comes from different assumptions regarding fertilizer prices and whether farmers sold maize directly after harvest or later in the season, when maize prices had risen, suggesting that policies which allow farmers to hold off on selling maize may be an effective means of increasing the expected profitability of fertilizer use.

Taken together, these essays underscore the role of factor market frictions and other imperfections in limiting input use among smallholders in sub-Saharan Africa. They highlight the need to consider the additional constraints farmers face as a result of these linkages as part of a strategy to increase agricultural production.

I dedicate this dissertation to my parents: Jay, John, and Lenore.

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KEY TO ABBREVIATIONS

AE	Adult equivalent
AEZ	Agro-ecological zone
Africa RISING	Africa Research in Sustainable Intensification for the Next Generation
AISE	Agricultural Input Supply Enterprise
AMIS	Agricultural Market Information System
APP	Average physical product
AVCR	Average value cost ratio
CAN	Calcium ammonium nitrate
CF	Control function
DAP	Diammonium phosphate
EA	Enumeration area
EPA	Extension planting area
ESS	Ethiopia Socioeconomic Survey
ETB	Ethiopian birr
FE	Fixed effect
FEWSNET	Famine Early Warning Systems Network
Ha	Hectare
IFDC	International Fertilizer Development Center
Kg	Kilogram
KSH	Kenyan shillings
LPM	Linear probability model
LSMS	Living Standards Measurement Survey

MPP	Marginal physical product
MVCR	Marginal value cost ratio
MWK	Malawi kwacha
N	Nitrogen
NPK	Nitrogen, phosphorus, potassium
NPS	Nitrogen, phosphorus, sulphur
OLS	Ordinary least squares
P	Phosphorus
SNNPR	Southern Nations, Nationalities, and Peoples' Region
SOC	Soil organic carbon
SOM	Soil organic matter
Total C	Total organic carbon

INTRODUCTION

Despite decades of targeted research and policy, agricultural input use in sub-Saharan Africa (SSA) remains low. In 2015, average rates of nitrogen applied through inorganic fertilizer were roughly 13.3 kg N/ha of cultivated land continent-wide, compared to 63.6 kg N/ha of cultivated land in Southeast Asia (FAOSTAT). Yields are also below those found in other tropical countries: in 2016, maize yields were estimated at 1.9 tons/ha, versus 3.7 tons/ha in Mexico in the same year (FAOSTAT); excluding yields on irrigated land reduces the gap somewhat but not completely (Smale et al. 2011) Furthermore, recent evidence suggesting that households in densely populated areas are unable to easily acquire additional arable land means that increasing production at the extensive margin is no longer an option for most smallholders (Jayne et al. 2014). As such, increasing modern input use in SSA continues to be a critical challenge facing policymakers and researchers.

Moreover, while it is increasingly understood that incomplete markets impose additional constraints on rural households, the role of factor market imperfections in limiting input use is under-studied. This dissertation, titled *Factor Markets, Relative Prices, and Input Use in Eastern and Southern Africa*, begins to fill this gap by exploring the link between agricultural factor markets, input use, and production in Eastern and Southern Africa, where land pressures and variability in production are particularly acute.

Since as early as the 1960s, large-scale input subsidy programs have been a dominant feature of agricultural policy and have comprised large agricultural budget shares in SSA (Kherallah et al. 2002, Jayne & Rashid 2013). The primary goal of these programs was to increase fertilizer and other input use by relaxing liquidity constraints and making fertilizer more widely available. The universal input subsidy programs, popular throughout the 1960s and

1970s, were largely phased out but have seen in recent years a resurgence in the form of targeted input subsidy programs, with parallel goals but aimed at certain types of farmers. Research in this area took a similar focus, and there is a large set of literature on variation in profitability of fertilizer use (e.g., Marenya & Barrett 2009, Sheahan et al. 2013) and availability (Jayne & Rashid 2013). At the same time, a similarly large set of literature assesses these input subsidy programs, with mixed conclusions as to their effectiveness in reaching their stated goals of increased input use and food security (e.g., Denning et al. 2009, Dorward & Chirwa 2011, Druilhe & Barreiro-Hurle 2012, Sachs 2012, with a synthesis in Jayne & Rashid 2013).

Distinct from work on agricultural intensification is a growing set of literature showing that smallholders face a myriad of additional constraints that result from incomplete markets. That is, due to interlinkages between markets, input demand does not only depend on prices and marginal products, but household characteristics and endowments, calling into question the wisdom of policies that aim to increase fertilizer use solely by lowering its price. Studies on incomplete markets have focused on the absence of insurance markets to protect against risky inputs (Karlan et al. 2014, Cole et al. 2017, Emerick et al. 2016), low access to information (Cole & Fernando 2016), and a lack of commitment devices to account for time-inconsistent preferences (Duflo et al. 2011).

This work, however, has not yet examined how the completeness of factor markets affects fertilizer use and farmers' response to changing input prices. This dissertation seeks to bridge the gap between the literature on agricultural intensification and that on missing markets using panel data from Ethiopia, Kenya, and Malawi.

The first chapter examines the relationship between fertilizer demand and agricultural labor markets by testing for separability in farm labor and conditional fertilizer demand. Building on the methods of Benjamin (1992) and LaFave & Thomas (2016), the intuition behind this test is as follows: if markets are complete, then farm households will behave as profit maximizers and make farm input decisions based solely on input and expected output prices and marginal products. Finding that household consumption preferences and factors that affect consumption preferences, including labor endowment, affect farm input demand implies that at least two markets are incomplete. This, in turn, implies that households may face additional constraints to input use--constraints that will not necessarily be relaxed by solely lowering prices.

Using three waves of the World Bank's Ethiopia Socioeconomic Survey (ESS) and relying on household-level fixed effects to control for characteristics such as farmer skill and land quality that may affect both input demand and household composition, I show that the share of working-age men in a household has a positive and significant effect on farm labor and conditional fertilizer demand. This holds when restricting the sample to households in which any changes in composition are solely due to aging, a strictly exogenous process, ensuring that these results are not driven by household members migrating into or out of the household in response to changes in input demand. For conditional fertilizer demand, the results are stronger among these households. Separability is rejected in both inputs, implying that imperfections in multiple markets affect farm labor and conditional fertilizer demand among these smallholders. Moreover, these results are consistent with there being frictions or other costs associated with participating in agricultural labor markets that lead to labor-constrained households using less farm labor and fertilizer.

The second portion of this chapter examines separability and farm input demand from a different angle by estimating the own- and cross-price elasticities of both inputs. This builds on analyses of the sort undertaken by Deaton (1989), Binswanger et al. (1987), as well as work by de Janvry et al. (1991) showing that incomplete market and non-separability can lead to counterintuitive demand price elasticities. Farm labor demand is relatively inelastic with respect to the market wage, providing further suggestive evidence of households not participating fully in agricultural labor markets. Among households with no migrant members, the own-price elasticity of conditional fertilizer demand is low, indicating that solely lower fertilizer prices is unlikely to greatly increase fertilizer use among certain types of households.

The second chapter extends this price elasticity analysis to examine Kenyan smallholders' response to changing land, labor, and fertilizer prices with a 13 year panel dataset collected by Michigan State University and Egerton University. This paper also contributes to recent work testing Boserup's (1965) hypothesis that, as population density increases and relative land and labor prices change as a result, households will shift away from using the relatively more expensive input towards the relatively cheaper one. I estimate the elasticities of demand for cultivated area and fertilizer with respect to input prices and rely on the inclusion of year fixed effects and district fixed effects to control for secular trends and district-level differences in land quality, growing potential, and market characteristics.

Demand for cultivated area, or production at the extensive margin, is relatively inelastic with respect to all input prices. Demand for fertilizer is similarly unresponsive with respect to land and labor prices, and this holds at both the household and field level, and with the inclusion of household fixed effects. Instead, households increase their use of fertilizer as its price decreases, and over time. Together, these results suggest that households are not responding flexibly to changes in land and labor prices, perhaps due to transactions costs or other market frictions.

While the first two chapters focus on constraints to fertilizer use imposed by incomplete or thin factor markets, the third chapter questions whether increasing fertilizer use is profitable for all farmers and examines more closely the linkages between soil characteristics, labor markets, fertilizer profitability, and maize yield. In Malawi, with one of the most widely recognized agricultural input subsidy programs, the government spent nearly $200 million on input subsidies annually over the past decade (Jayne & Rashid 2013)—over half of its agricultural spending—but which resulted in only moderate yield increases (Dorward & Chirwa 2011). Despite these heavy subsidies, use of inputs remain low, and estimated maize response rates to fertilizer vary widely across studies, raising questions about the source of this variability and whether fertilizer is generally profitable for most smallholders when valued at market prices.

This chapter uses survey and soil data from farmers' self-identified most and least fertile maize plots in Central Malawi to explain the heterogeneity in maize response to inputs and to determine whether this heterogeneity explains low uptake of commercial fertilizer. I estimate maize response functions using plot-level fixed effects to characterize the range of maize response to fertilizer and weeding labor within extension planting areas (EPAs) and show that these differences in productivity are not solely attributable to farmer skill, with differences in productivity persisting even with the plot-level fixed effects. Using a range of price scenarios and classifying soil fertility according to total organic carbon levels, I find that weeding labor is significantly more profitable on the most fertile plots in our sample, despite the two receiving comparable rates. Conversely, fertilizer is significantly more profitable on the least fertile plots, despite being applied at higher rates than on the most fertile plots.

Perhaps unsurprisingly, the largest variation comes from differences between price scenarios, rather than from differences in plot and soil characteristics. In particular, the expected profitability of input use increases considerably when farmers are able to hold off until selling maize until prices have increased. This suggests that policies which allow farmers to do so, such as improved storage options and development of rural labor markets for additional income sources, may be effective in increasing the expected profitability of fertilizer use.

Taken together, these essays underscore the fact that fertilizer use is predicated on other markets and that the completeness of these markets affects fertilizer use independently of price. This suggests that policies which account for interlinkages in production are more likely to be effective in increasing fertilizer use than those which do not.

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1 AGRICULTURAL LABOR MARKETS AND FERTILIZER DEMAND: INTENSIFICATION IS NOT A SINGLE FACTOR PROBLEM FOR NON-SEPARABLE HOUSEHOLDS

1.1 Introduction

With a growing population that relies on a fixed quantity of arable land, the only option for most smallholder farmers in sub-Saharan Africa is to increase output through intensification on land they already cultivate (Jayne et al. 2014). In many countries, however, use of yield-increasing inputs such as fertilizer remains low. One common explanation is that fertilizer is too expensive for farmers to obtain or use profitably. Yet binding financial constraints do not sufficiently explain the low fertilizer application rates seen throughout sub-Saharan Africa. As is known from theory and shown by Feder (1985), Singh et al. (1986), and others, if a household is prevented from participating in a single market, it can reallocate resources so it first maximizes expected farm profits, then chooses consumption levels accordingly. If all markets but those for credit are complete and accessible, then households should be able to rent out or sell land or labor for income to purchase other inputs.

Despite this reasoning, national policy aimed at raising fertilizer use often focuses on a single dimension: relaxing financial constraints through large-scale input subsidy programs. Similarly, while there is widespread recognition among researchers that missing or incomplete markets can prevent farmers from adopting a new technology,[1] the literature has neglected examination of their role in limiting input use at the intensive margin. Studies focus on the role of plot and farmer characteristics in variation in profitability of fertilizer use (Marenya & Barrett

[1] See, for example, Sunding & Zilberman (2001) for a review.

2009, Sheahan 2011), difficulties in access and timing of availability (Jayne & Rashid 2013), and time-inconsistent preferences (Duflo et al. 2011). While this work is critical to understanding low fertilizer use in sub-Saharan Africa, it overlooks the possibility that problems in other markets may prevent farmers from scaling up production, even when fertilizer is heavily subsidized.[2]

In this paper, I begin to fill this gap in the literature on intensification by testing whether imperfections in factor markets affect agricultural labor and conditional fertilizer demand. I link recent work which tests for complete markets in Indonesia (LaFave & Thomas 2016) and sub-Saharan Africa (Dillon & Barrett 2017; Dillon et al. 2017) with empirical work on agricultural intensification. Conceptually, it is reasonable to expect that market imperfections would affect input demand at the intensive margin, not just the extensive margin. Yet studies on market imperfections do not discuss the implications for production, while those on intensification typically do not discuss the implications of market imperfections. This paper's primary contribution is to bridge this gap.

There is a large body of historical evidence which shows that imperfections in multiple markets affect an agricultural household's production decisions. Chayanov (1926) and Sen (1966) noted that the shadow price of labor may be endogenously determined among smallholders, who maximize utility rather than profits. In their canonical work, Singh et al (1986) show that, when multiple markets are missing or incomplete, the agricultural household's endowments of land and labor help determine its production decisions. When this is the case, input demand no longer depends solely on input and output prices, but also on household consumption preferences and endowments. That is, imperfections in multiple markets cause the

[2] One notable exception is Karlan et al (2014), who find that incomplete insurance markets limit agricultural investment in northern Ghana.

agricultural household's problem to be non-separable. For example, a farm household's labor demand will depend on the number of family members able to work, or the area of land it cultivates will depend on the quantity it owns.

In addition to theoretical work showing how incomplete markets will change households' production decisions, there is considerable empirical evidence that, in many parts of the developing world, markets are in fact incomplete. This includes work on incomplete credit and insurance markets (e.g., Townsend 1994; Berg 2013; Karlan et al. 2014; Beaman et al. 2015), as well as evidence on thin or imperfect land and labor markets (e.g., Collier 1983; Lopez 1984; de Janvry et al. 1991; Sadoulet et al. 1998).

In line with this evidence, the implicit assumption of incomplete markets is common in the intensification literature, which typically models a household's problem as being non-separable. Yet empirical evidence on the degree to which this assumption holds is ambiguous. For example, several papers in a recent Food Policy Special Issue on intensification include household size and other characteristics in estimating fertilizer demand functions (Ricker-Gilbert et al. 2014; Josephson et al. 2014; Headey et al. 2014; Muyanga & Jayne 2014). In these studies, certain household characteristics, such as the education level of the household head, are significant. Household size and adult equivalents are not. Similarly, Ricker-Gilbert et al. (2011) and Xu et al. (2009) include household composition and characteristics in their models of demand for commercial fertilizer in Malawi and Zambia, respectively, but in neither study is household composition a significant predictor of fertilizer demand. In Alene et al.'s (2008) study of maize supply and fertilizer demand in Kenya, household size positively impacts households' participation in maize markets, while its effect on fertilizer adoption and demand is insignificant. At the same time, evidence from Ricker-Gilbert et al. (2009) in Malawi and Sheahan (2011) in

Kenya shows that input subsidies may result in overapplication of inputs, which suggests that input market failures may *not* constrain production. The ambiguity in empirical work highlights the need to examine both the assumption and implications of non-separable models more closely.

This paper's first contribution is thus to test for separability in farm labor and conditional fertilizer demand by building on the approach of Benjamin (1992) and LaFave & Thomas (2016). This approach is driven by the observation that, if markets are complete, farm input demand should only depend on prices and technical relationships. Household composition, which helps determine household labor supply and consumption preferences, should play no role in production decisions.

Using nationally representative household-level panel data from Ethiopia, I draw on LaFave & Thomas's (2016) method and test whether an exogenous shock to household composition—aging of household members—affects the household's agricultural labor demand. Restricting the sample accordingly ensures that my results are not driven by endogenous household composition changes, such as if household members migrate due to low labor demand. I also extend their approach to test for the effect of household composition on fertilizer demand among fertilizer users. I find that total farm labor and conditional fertilizer demand increase with household labor supply. All else equal, a one standard deviation increase in the share of working-age males in a household with no migrant members would increase total labor demand by 18.3% of its wave 1 standard deviation and total conditional fertilizer demand by 41.6% of its wave 1 standard deviation. Separability is rejected in total agricultural labor demand and total conditional fertilizer demand, though I fail to reject that household composition has no effect on demand per hectare for either input.

While a rejection of separability in itself says nothing about whether markets are failing, or where the problems may be, it does imply that households are not fully participating in markets. As noted by de Janvry et al. (1991), this means there are imperfections in multiple markets. High frictions and other market imperfections, in turn, can cause inefficiencies and misallocation, and, ultimately, lower productivity (Adamopoulos et al. 2017, Jones 2011a). Similarly, due to linkages and complementarities in input use and markets, the additional constraints households face as a result of incomplete markets will spill over into other production decisions (Jones 2011b, Kremer 1993). As such, policy interventions that do not account for these linkages and incompleteness be significantly less effective (Taylor & Adelman 2003).

This paper's second contribution is therefore to examine how households adjust their farm labor and conditional fertilizer demand in response to changing input prices. Doing so builds on the work of de Janvry et al. (1991), who show that imperfections in multiple markets can decrease the degree to which households respond to price changes, or even change the sign of the response. It can also help identify households' primary constraints and, thus, where policy changes will have the greatest impact. As Deaton (1989) argues, this type of analysis is a necessary component of any discussion of policy implications.

This approach fills a key gap in the intensification literature, which has recently focused on how rising population density changes relative factor prices, and how these changing prices affect intensification. Fertilizer prices and wage rates enter into this question, but neither they nor local labor markets are the primary focus. For example, several of the previously mentioned papers on intensification showed that wage rates have a negative (though not necessarily statistically significant) impact on fertilizer use (e.g., Muyanga & Jayne 2014; Ricker-Gilbert et al. 2014; Josephson et al. 2014).[3]

In the second portion of this paper, I find low elasticity of agricultural labor demand with respect to market wages, at -0.08, among households with no migrant members. This suggests that households are not participating fully in agricultural labor markets and is consistent with both the separability results as well as ex ante evidence that households rely primarily on their own labor supply for on-farm work (Bachewe et al. 2016). Among the same households, I also find that conditional fertilizer demand is relatively inelastic with respect to fertilizer prices, at -0.09. This suggests that policies which solely lower fertilizer prices will, at best, only marginally increase fertilizer use among these households. Fertilizer demand among all households has a positive elasticity with respect to market wages, at 0.06, though the effect is not statistically different from zero. Together, the elasticity results, coupled with the separability results, highlight the need for policies which focus on interlinkages between input use and markets as part of a strategy to increase fertilizer use.

Identification hinges on delinking choice variables that are endogenous to fertilizer and agricultural labor demand—namely, household composition, area cultivated, and crop choice. In testing for separability, as well as estimating cross-price elasticities, I follow the approach of LaFave & Thomas (2016) and implement a number of sample restrictions to assess the validity of treating these variables as exogenous. For both fertilizer and labor demand, the overall pattern of results is robust to restricting the sample to households in which any composition changes were strictly exogenous. In fact, the separability results are stronger among these households.

[3] While these studies are important contributions to our understanding of smallholders' responses to rising population density, their focus differs from this paper's, and the implications for intensification from the price results are not discussed.

The rest of the paper proceeds as follows: the next section presents a conceptual framework of an agricultural household's maximization problem. Section 1.3 discusses input and output markets in Ethiopia, and section 1.4 describes the data. Section 1.5 discusses the empirical and identification strategies. Section 1.6 presents the results for the tests of separability, section 1.7 discusses the price elasticity analysis and results, and the final section concludes.

1.2 Conceptual framework of an agricultural household

1.2.1 Utility maximization with a single missing market

In the model pioneered by Singh et al. (1986), the agricultural household cultivates crops not just for sale, but also for consumption. This means that consumption depends directly on how much is produced. When markets are complete and households can obtain or earn income from land, labor, and other inputs as desired, the household will first allocate inputs to maximize profits from production, then make its consumption decisions. Households which have an excess supply of any input are able to rent it out or sell it, while those with excess demand can purchase or rent it in at market prices.

In the case of a failure in a single market, the household can reallocate resources, and its optimization problem will remain recursive (Feder 1985). When there are imperfections in multiple markets, the household is unable to do so, and farm input demand will depend not just input and output prices and technical relationships, but also on consumption preferences and relative endowments of land and labor. That is, the household's problem is no longer separable (Benjamin 1992; Udry 1999). Testing for separability between farm production and household consumption decisions thus amounts to testing for complete markets.

To test whether separability holds in input demand, I begin with a single period agricultural household model, as given by Singh et al. (1986) and Benjamin (1992), and the assumption that all markets are complete, except for a missing credit market. Under these conditions, a household with an endowment of labor $\bar{L}$ and land $\bar{A}$ will seek to maximize its utility in a given period by solving:

$$\max U(c, l; \mu, \varphi) \text{ subject to} \tag{1}$$

$$\pi = p^y y - wL - rA - p^z Z \tag{2}$$

$$y = f(L, Z, A; \theta) \tag{3}$$

$$L = L^F + L^H \tag{4}$$

$$A = \bar{A} - A^O + A^i \tag{5}$$

$$\bar{L} = l + L^O + L^F \tag{6}$$

$$p^y c + wl \leq \pi(w, r, p^z, p^y; \theta) + w\bar{L} + rA^O \tag{7}$$

That is, a household with observed characteristics μ and unobserved characteristics φ maximizes its utility from consumption of the agricultural good c and leisure l through profits π obtained through production of the same agricultural good, y, with its corresponding market price p^y. It does so by allocating land A, labor L, and fertilizer Z, with a production technology that depends on these inputs and exogenous shocks θ.

Labor used in production is the amount of time spent working by household members on the farm, L^F, added to that spent by hired laborers L^H. The quantity of land used in production, A, is assumed to be the household's initial endowment of land $\bar{A}$, less that which is rented out A^O, added to that which is rented in A^i. The household divides its time endowment, $\bar{L}$, between time spent in leisure l, on-farm work L^F, and off-farm work L^O.

Finally, the household's budget constraint, as given in equation (7), indicates that, in the absence of credit markets, households are unable to borrow to let their consumption exceed their income. Household income, the right hand side of equation (7), is a combination of farm profits and income earned from the household's labor—its time endowment less the time spent in leisure—and the renting out of land.

Under this recursive problem, the household first maximizes farm profits, then chooses its consumption of leisure and the agricultural good to maximize its utility. First order conditions from the profit maximization problem imply that farmers will use a given farm input up to the point where its marginal product is equal to its price divided by the output price. Hired and family labor are assumed to be perfectly interchangeable. The household values its own labor at the market wage, because the opportunity cost of leisure is simply the wage that could be earned working on or off the farm. That is, the household's shadow wage equals the market wage.

These first order conditions imply that demand for farm labor and fertilizer depend only on input prices, the output price, and weather conditions:

$$L^* = L^*(w, r, p^z, p^y; \theta) \tag{8}$$

$$Z^* = Z^*(w, r, p^z, p^y; \theta) \tag{9}$$

1.2.2 Utility maximization with imperfections in multiple markets

When multiple markets are incomplete or missing, the agricultural household's problem is no longer separable, and its production decisions will not be made independently of its consumption decisions. To demonstrate how labor market imperfections could affect demand for both farm labor and fertilizer, I build on Benjamin's (1992) approach and the model described above and examine three scenarios. In the first scenario, off-farm employment is limited, so that households cannot supply more than $\bar{O}$ of off-farm labor. In the second, hired labor is capped at

$\bar{H}$. In the third, differential search or monitoring costs mean that households either face lower returns to off-farm labor, or that hired labor is more costly than on-farm family labor.

1.2.2.1 Off-farm employment capped at $\bar{O}$

Following standard models of labor supply, the household's supply of labor to both off-farm and on-farm work L^S is given by:

$$L^S = \bar{L} - l(w, M;\ \mu, \varphi) \tag{10}$$

Where $M = \pi + w\bar{L} + rA^O$, the right hand side of equation (7), and is the household's full income constraint. For some households, $L^S \geq L^*(p^Z, w, r, p^y; \theta) + \bar{O}$—that is, labor supply will exceed the profit-maximizing level of farm labor plus available off-farm work.[4] Households for whom this holds will supply more labor on the farm than they would if labor markets were complete and will supply labor up to the point where $f_L(L, Z, A;\ \theta) = w'$, where *w'<w.* That is, these households will supply labor up to the point where its marginal return is equivalent to the shadow wage, *w'*. These households will also not hire in any labor, since *w>w'*. Moreover, since there is no hired labor, the shadow wage is determined by equating the household's labor supply with the sum of farm labor demand and off-farm employment, or finding the *w'* for which $L^S = L^F + \bar{O}$. Intuitively, households with a higher labor endowment will supply more labor, which will drive down the shadow wage.

In this case, both the household's farm profits and budget constraint will also be affected. For households that would have supplied $L^O > \bar{O}$, they are now given by:

$$\pi' = p^y y - w' L^F - rA - p^z Z \tag{2'}$$

$$p^y c + w' l \leq \pi(w', r, p^z, p^y; \theta) + w'(\bar{L} - \bar{O}) + w\bar{O} + rA^O \tag{7'}$$

[4] For others, it will not, and these households will solve a recursive optimization problem, as in section 1.2.1.

Since *w'* < *w* and $\bar{O} < L^O$ for these households, overall consumption—including, potentially, expenditure on farm inputs—will decrease. Among households which relied on income to finance fertilizer purchases in the absence of credit markets, this would also decrease fertilizer demand. Moreover, as the household's labor supply is increasing in its labor endowment, while the shadow wage is decreasing in labor supply, we would expect households with a higher labor endowment to use more farm labor. That is, $\partial L^F / \partial \bar{L} > 0$.

1.2.2.2 Limited availability of hired in labor

Suppose, instead, that there is a limited quantity of hired labor available. For some households, this limit, $\bar{H}$, will be low enough that $\bar{H} + L^F < L^*$.[5] That is, these households have neither sufficient family labor nor can hire in sufficient outside labor to meet profit-maximizing farm labor demand. In this case, households will hire in as much labor as they can, $\bar{H}$. Since $\bar{H} < L^*$, households will also apply family labor up to the point where $f_L(L, Z, A; \theta) = w'$.

As in the previous scenario, the shadow wage is determined by the household equating total labor supply—family labor supply plus hired labor—to farm labor demand. That is, *w'* is the wage at which $L^S = L^D + \bar{H}$. In this case, however, *w'* > *w*. Intuitively, households have the option of working off the farm to earn *w*, so they will only supply labor on the farm if $w' \geq w$.

Furthermore, since some households in this scenario are labor-constrained, total observed farm labor will be increasing in the household's labor endowment in this scenario. Formally, farm profits are given by:

$$\pi'' = p^y y - w' L^F - w\bar{H} - rA - p^z Z \tag{2''}$$

[5] As in the preceding scenario, households for whom this does not hold will still solve a recursive optimization problem.

Moreover, given that labor and fertilizer are complements in production, an increase in the shadow wage—the cost of labor—will result in lower fertilizer use, i.e., $\partial Z/\partial w < 0$. Intuitively, if households are labor-constrained, the use of labor-intensive inputs, such as fertilizer, will decline. In this instance, we would again expect both farm labor and fertilizer demand to be increasing in the household's labor endowment.

1.2.2.3 Differential search and monitoring costs

There are of course other reasons why households may value their own on-farm labor differently from that of hired laborers. Two such examples are when it is either costly for household members to find off-farm employment, or if it is costly to find and monitor hired laborers.

Case 1: High costs to obtain off-farm employment

In this case, the household's off-farm wage can be defined as $w^O = w - g(TC)$, where *g(TC)* denotes search and other transactions costs associated with finding off-farm work. In this case, farm profits are unchanged from equation (2), but the household will only receive $w^O L^O$ from off-farm work. Farm labor demand in this case will not depend on household labor endowment, since hired and family labor are still perfectly interchangeable. Given that the household's overall labor supply is still increasing in its labor endowment, its income from off-farm work will increase with its labor endowment. In the absence of credit markets, this will potentially relax a cash constraint in purchasing fertilizer.

Case 2: High search or monitoring costs associated with hired labor

If instead it is costly for households either to find hired laborers, or if hired laborers will not work hard on the farm unless well-monitored, the total cost of a hired laborer can be given as $w^O = w + h(TC)$, where *h(TC)* denotes the search or monitoring costs. Farm profits are now given by:

$$\pi''' = p^y y - w'L^F - w^H L^H - rA - p^z Z \qquad (2''')$$

In this case, it will be less costly for the household to use its family labor over hired labor. This means that total labor demand will be increasing in household labor supply. Moreover, since fertilizer and labor are complements in production,[6] and since labor costs are decreasing in family labor supply, fertilizer demand will increase with family labor supply. Since labor supply is increasing in labor endowment, so will fertilizer demand.

1.2.2.4 Input demand with market imperfections

As shown in the preceding section, with differential search and monitoring costs, the household's input demand may be increasing in its labor endowment. Moreover, equations (2') and (2'') both imply that, with market imperfections, farm profits will no longer depend solely on exogenous market prices and weather conditions, but will instead also depend on the household's shadow wage. Generalizing the two scenarios described in sections 1.2.2.1 and 1.2.2.2 above, when the household's shadow wage does not equal the market wage, farm profits are given as:

$$\pi'''' = p^y y - w'L^F - wL^O - rA - p^z Z \qquad (2'''')$$

[6] It takes labor to apply fertilizer, and fertilizer use generally results in more weed growth, which requires more labor to manage (Kamanga et al. 2014)

Taking first order conditions of (2'''') with respect to total farm labor, L, and fertilizer Z and some rearranging yields the following input demand functions:

$$L^{**} = L^{**}(w', w, r, p^z, p^y, M'; \theta, \mu, \varphi) \quad (8')$$

$$Z^{**} = Z^{**}(w', w, r, p^z, p^y, M'; \theta, \mu, \varphi) \quad (9')$$

Where both labor and fertilizer demand now depend on the household's shadow wage which, as described above, depends on household characteristics and preferences, including its labor endowment, as well as its income (denoted by *M'* to differentiate between the full income constraint under profit maximization).

To summarize the models described above, when markets are complete, or in the case of a single missing market, farm households behave as profit-maximizers. When multiple markets are incomplete, households' production decisions change, and they may no longer use inputs at the same rate as if markets were complete. As I discussed in the preceding sections, this means that different types of labor market failures could lower fertilizer use, even if fertilizer markets themselves remain unchanged.

1.2.3 Demand response to changes in input prices

Another implication of households not fully participating in factor markets is that they may respond to price changes in counterintuitive ways. This is described at length by de Janvry et al. (1991), who show how imperfections in food or labor markets explain low supply response to changes in cash crop prices in sub-Saharan Africa. By extension, it is possible that smallholders' demand responses to changing input prices are different from what is predicted by economic theory.

In a separable model, an increase in any input price will increase production costs, which will decrease input use. The household will also shift away from use of the more expensive input and complementary inputs towards its substitutes, meaning that the demand response of an input, with respect to price changes for its complements, is unambiguously negative. With complete markets, we would expect a strong, negative cross-price elasticity of fertilizer or labor demand with respect to the price of the other. As mentioned above, this is because fertilizer and labor are complements in production.

In a non-separable model, this might not hold. A wage change will affect the agricultural household both as a producer, but also as a group of laborers who can earn income from wages. As shown in equations (8') and (9'), this will affect production decisions, including fertilizer demand.

How, exactly, a wage change affects fertilizer demand depends on a number of factors. Two of these factors are the household's binding constraints in fertilizer use and whether the household is a net buyer or seller of labor. For example, if there are limited off-farm employment options, as in section 1.2.2.1, then net sellers of labor would see a (weak) increase in off-farm income from an increase in wage. This increase in income would relax a binding liquidity constraint, and fertilizer demand could increase with off-farm wages. For net buyers of labor (who are, presumably, constrained in labor), an increase in market wages would increase production costs and the opportunity cost of working on the farm. Combined, this would result in reductions in both on-farm labor and fertilizer use.

How households ultimately respond to price changes can help guide policy. Price elasticities indicate the underlying tradeoffs in input use and can point to where farmers may be most constrained.

1.3 Input markets in Ethiopia

The institutional context of land and fertilizer markets in Ethiopia differs somewhat from those in neighboring countries. The government has undergone a series of drastic regime shifts in the past 50 years, ranging from a hands-off imperial regime from 1960-1974, to a period of heavy intervention by the socialist government (1975-1990), and to subsequent market liberalization. Throughout this time—since the socialist government—land has been controlled by the state, and households currently receive certificates which allow them to use, rent out, or bequeath land, but not sell it (Ambaye 2015). Land leasing is legal and the market active (Teklu & Lemi 2004; Holden & Ghebru 2006; Pender & Fafchamps 2006; Deininger et al. 2008, and others), though frictions and high transactions costs in land lease markets have been found in Tigray (Ghebru & Holden 2008) and Amhara (Deininger et al. 2008). The presence of these frictions and transactions costs suggest barriers to participation in land rental markets, which would be consistent with non-separability.

Fertilizer was introduced to Ethiopia to the four major grain-producing regions—Oromia, SNNPR, Tigray, and Amhara—in the late 1960s (Rashid & Negassa 2011; IFDC 2012). Private fertilizer companies never held a large market share, and, even following the end of the socialist regime in 1990, fertilizer has remained a largely state-controlled good, with all fertilizer imports coordinated through the state-run Agricultural Input Supply Enterprise (AISE) (Rashid et al. 2013).

Farmer cooperatives are heavily involved in fertilizer acquisition. Every year, fertilizer acquisition begins at the *kebele* level, where farmers state their estimated demand for the upcoming growing season. These estimates are aggregated up administrative divisions until they reach the AISE, which decides how much fertilizer to import. This quantity is imported and then passed back down the chain (IFDC 2012). A comparison of fertilizer prices in neighboring countries shows that Ethiopia's prices are somewhat lower, suggesting a blanket government subsidy that is enjoyed by all farmers purchasing fertilizer (Rashid et al. 2013). Cereals account for 90% of fertilizer use, with the bulk of it being applied to three crops: teff, wheat, and maize (IFDC 2012).

It is difficult to say, *ex ante*, whether the structure of fertilizer markets in Ethiopia suggest they may be incomplete. Ethiopia has not been the subject of reports, as in neighboring countries, of input subsidies which benefit a select group of farmers,[7] and fertilizer appears to be available to any farmer who wants to use it. This suggests that any barriers to fertilizer use are not caused by problems in the fertilizer market, but instead by problems in other markets (e.g., credit). On the other hand, fertilizer markets are clearly not competitive, with a single actor—the government—controlling prices and sales.

In contrast with fertilizer and land markets, agricultural labor markets in Ethiopia are relatively neglected, with only a few, mostly dated works (e.g., Holden et al. 2004; Dercon & Krishnan 1996; Block & Webb 2001). An exception is Bachewe et al. 2016, who find that rates of hired in agricultural labor vary systematically with household landholdings and demographic characteristics, particularly the age, gender, and education level of the household head.[8] Although they do not explicitly test for it, their findings are consistent with a rejection of separability. They also find that the share of hired in labor decreases with distance to the capital, Addis Ababa, which suggests spatial differences in agricultural labor markets. More recently,

[7] For example, wealthier and better-connected farmers have been found to be more likely to receive input subsidy vouchers in Malawi (Dorward & Chirwa 2011)

[8] Though rates of hiring in are low, with 76% of households in their survey of the four major grain-producing regions relying solely on family labor.

Dillon et al. (2017) reject separability and find that poor households in Ethiopia experience agricultural labor shortages, while wealthier households have an excess supply.

1.4 Data

To test whether separability holds in agricultural labor and fertilizer demand, I use data from the three waves of the World Bank's Ethiopia Socioeconomic Survey (ESS). A nationally representative panel survey, the first wave (2011/12) included only rural households, while those in small towns and urban areas were added in subsequent years (2013/14 and 2015/16). The survey covered 290 rural and 43 small town enumeration areas (EAs) in all regional states except for the capital, Addis Ababa, with an additional 100 major urban area EAs added in the second and third waves. While attrition was low—of the 3,969 households interviewed in the first wave, 95% were tracked through the second and third waves—I restrict the sample to rural households which were interviewed and cultivated land in all three waves to mitigate attrition bias and to focus on households for which farming is a primary livelihood. I also drop households in regions where fertilizer use and accessibility are low—Afar, Somalie, Gambela, Harari, Benishangul-Gumuz, and Dire Dawa—as this provides a different set of constraints than those faced by a farmer in an area where fertilizer is widespread, relatively easily obtainable, and has been used for decades. This leaves a total of 1,732 rural households which cultivated land and have had access to fertilizer since the 1960s.

Demographic data, including household composition, was obtained directly from the surveys and was cross-checked across years to ensure accuracy. So as to avoid skewing of results by outliers, I drop households in the top 99th percentile of landholdings, which is 7 hectares.

I model fertilizer demand as the quantity of fertilizer actually applied, as measured at the plot level, and pooled across fertilizer types (DAP, urea, and NPS). While this aggregation masks differences in fertilizer nutrient content—such as varying levels of nitrogen by fertilizer type—further disaggregation is not feasible for two reasons. First, farmers were asked not just about the quantities of DAP and urea applied separately, but also about the quantity of a mixture of the two that was applied. Since the relative ratio of the two fertilizers in the mixture was not reported, it is impossible to accurately calculate how much DAP and urea were applied individually. Second, NPS fertilizer was brought to Ethiopia between the second and third survey waves. This means that farmers in the first two waves were unable to use it, while those in the third wave likely substituted use of the other two fertilizer types with NPS. Disaggregating fertilizer demand by type would require accounting for these substitution effects.

Agricultural labor demand was also measured at the plot level, which I then aggregate up to the household level. This aggregation includes all types of laborers—household men, women, and children, as well as hired laborers—and all activities (planting, weeding, fertilizing) except for harvesting, as harvest labor is generally proportional to production and occurs when production is complete. I adjust the time spent working by children under the age of 12 by one half to account for child labor being less productive than adult labor. The time spent working by each household member is recorded in hours per day, days per week, and number of weeks, while hired labor is measured in days. As such, I calculate the total number of hours provided by household members and divide it by 6, the median hours per day worked over all three waves, so that all labor inputs are measured in days.

In addition to demographic and agricultural information, price data can be obtained from the surveys. Price data for market goods—agricultural output and inorganic fertilizer—was collected at the community level, while wage and land rental data were collected from farmers who participated in those markets. In both instances, households were not asked about a going rate for either input, but what they paid (or received). Due to data restrictions, I calculate land rental rates from households which rented in land for a season and from that calculate zone-level medians (moving to the region level when data was either missing or implausibly high or low). For fertilizer, cereal, and labor prices, I begin with an EA-level median and moved to the next highest administrative division in cases of missing or implausible data.

Finally, the LSMS team matched household GPS coordinates with geoclimatic and other geo-referenced data, which contain temperature and rainfall data. Descriptive statistics for the variables used in the analysis are shown in table 1.1.

Table 1.1: Wave 1 summary statistics of variables used in analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
Input demand					
Total labor demand (person days)	1,732	151.4	163.6	9	1135
Labor demand (person days/ha)	1,678	188.6	217.0	6.2	1538
Hired labor demand (person days)	1,732	7.0	31.8	0	580
Cond. fertilizer demand (kgs applied)	890	59.7	45.7	5	217
Cond. fertilizer demand (kg/ha)	890	62.3	86.6	0.8	1114
Area cultivated (ha)	1,729	1.1	1.0	0.05	6.37
Household characteristics					
Number of male HH members ages…					
Under 12	1,732	1.1	1.1	0	6
12-19	1,732	0.6	0.8	0	4
20-64	1,732	1.0	0.7	0	7
65+	1,732	0.1	0.3	0	1
Number of female HH members ages…					
Under 12	1,732	1.0	1.1	0	6
12-19	1,732	0.5	0.7	0	4
20-64	1,732	1.1	0.5	0	5
65+	1,732	0.1	0.2	0	1
Household size	1,732	5.4	2.1	1	14
Landholdings (ha)	1,732	1.1	1.0	0	6.4
Prices and rainfall					
Wages (nominal ETB/day)	1,732	22.3	8.2	8.3	50
Fertilizer prices (nominal ETB/kg)	1,732	11.1	1.9	6	18
Land rental rates (nominal ETB/ha/season)	1,732	2,356.5	1,217.8	954.3	5956.9
Annual rainfall (mm)	1,732	753.1	237.5	332	1295

Note: Conditional fertilizer demand excludes zero values. Differences in sample size are due to trimming cultivated area.

1.5 Estimation and identification strategies

1.5.1 Demand functions

1.5.1.1 Labor demand

As described in section 1.2 above, a key restriction implied by separability and the hypothesis of complete markets is that input demand only depends on observed market prices and technical relationships. Household characteristics, preferences, and composition, which affect the household's shadow wage, should not impact input demand. To test this restriction, I follow the approach of Benjamin (1992) and LaFave & Thomas (2016) and include variables for household composition and other characteristics in estimating linear approximations of the input demand functions given in (8') and (9'). First, I estimate labor demand L of household i in community j and time t as:

$$\ln L_{ijt} = \beta_0 + \sum_{n=1}^{4} \beta_1^n M_{ijt}^n + \sum_{n=1}^{4} \beta_2^n F_{ijt}^n + \beta_3 \ln X_{ijt} + \beta_4 \bar{A}_{ijt} + \eta_i + \vartheta_{jt} + \tau_t + \varepsilon_{ijt} \tag{11}$$

Household composition is the restriction of interest and is included as the share of males (N^M) and females (N^F) in specific age groups which I discuss in greater detail below. In a recursive model, where markets are complete, the household's shadow wage should equal the market wage, so household composition would have no effect on input demand, and neither β_1 nor β_2 would be statistically different from zero. Conversely, finding that either one or both are significantly different from zero suggests there is a differential between the shadow and market wages and amounts to a rejection of the null hypothesis of separability and complete markets. Moreover, as described in section 1.2.2, we would expect that, in certain circumstances that lead to the shadow wage differing from the market wage, input demand would be increasing in household labor endowment—as given by β_1 and β_2. That is, β_1>0 and, depending on whether female household members supply labor, it is possible that β_2 >0.

Identification of β_1 and β_2, however, requires controlling for other household characteristics that are likely correlated with household composition and that can affect input demand. Larger households are generally wealthier, and wealthier households tend to be better educated, which can affect the ways in which information is obtained and processed (Schultz 1975). Both household wealth and education levels can affect demand for fertilizer, an inherently risky input, as well as other cultivation decisions, which ultimately affect input demand in general. Larger households also generally own more land, and the land they own is typically of better quality—which affects profitability of input use and, thus, total input demand. Identification of the effect of household labor endowment on input demand, as distinct from its effect through a positive correlation between household wealth and landholdings, thus requires controlling for these factors.

For this reason, I include landholdings directly, as $\bar{A}$, and household size, X. Given that landholdings comprise the bulk of smallholders' assets, I assume that including landholdings also controls for household wealth. I also follow the approach of LaFave & Thomas (2016) and estimate the input demand functions using household-level fixed effects, included in equation (11) as η. Doing so differences out the time-invariant household characteristics which may be correlated with household size and composition, like the household head's gender, education level, and religion, as well unobservable characteristics, such as farmer experience and risk aversion. This is a slight departure from other work on non-separable household models, which has typically relied on inclusion of observable characteristics for identification of the household composition term, but fail to account for unobservable characteristics.

Given that households, for the most part, cultivate the same plots year after year, aggregating at the household level absorbs time-invariant plot characteristics, such as land quality, that are likely to affect input demand and also be correlated with household size, thus providing another potential source of bias. While aggregation at the household level does not allow for identification of differences between plots, it ensures that results are not driven by substitution of inputs between plots over time—for example, if farmers practice crop rotation.

Input demand also likely depends on area-specific shocks, such as rainfall and temperature, and this is accounted for with a community-time fixed effect, ϑ, which also absorbs input prices, expected output prices,[9] and other time-varying community-level characteristics. Including a community-time fixed effect also accounts for characteristics of labor, land, credit, fertilizer, and crop markets that could change over time. Similarly, the year fixed effect, τ, controls for yearly, country-level trends.

With household fixed effects, household composition is identified by changes in the share of members within a given gender-age group. Given the relatively short panel length—five years—age groupings that are coarse may not have sufficient variation for identification. Conversely, age groupings that are too narrow may have too few non-zero observations. My preferred configuration is based on life cycle effects and the distribution of ages of landholders. It has a total of 8 groups: males (or females) under age 12, those ages 12-19, those ages 20-64, and those ages 65 and up. That is, I group together young children who are unlikely to provide any meaningful labor, then adolescents who may be working on the family farm but are not providing the bulk of the labor, then working-age adults, then the elderly. With an average life expectancy of 64.5 in Ethiopia in 2015, it seems safe to assume that the majority of people in the final age group are unable to work at the same intensity as those in the younger groups.

As robustness checks, I modify the configuration used by LaFave & Thomas (2016) and use the following age groups: under 12, 12-19, 20-34, 35-49, 50-64, and 65 and up. This somewhat more flexible specification also separates young adults (20-34) who are more likely working on someone else's land than their own[10] from adults (35-49 and 50-64) who are likely

[9] This approach makes the simplifying assumption that all households form expectations about output prices in the same way.

[10] The earliest age at which anyone in the survey owned land is 20, and the median age of a landholder is 35.

working in their own land, and from the elderly (age 65 and up). Finally, I pool adults (ages 20 and up), again disaggregating by gender.

While the configuration used by LaFave & Thomas (2016) has the benefit of not imposing the assumption that, say, a 20 year old man has the same effect on input demand as a 50 year old man, my preferred specification, which pools males (or females) age 20-64, has two distinct advantages. First, there is an average of just one male age 20-64 in the households in the sample. This means that a given household is more likely than not to have no male members in the 20-34 category, the 35-49 category, or the 50-64 category.[11] This lack of variation is potentially problematic for identification. The second advantage of my preferred specification is that it returns a single point estimate for the share of working-age males—the household's labor supply. The single point estimate makes it easier to interpret the results in a wider context of how changes in labor supply can affect input demand.

1.5.1.2 Fertilizer demand

I next extend the model from equation (11) to estimate the effect of household composition on fertilizer demand but impose additional restrictions to deal with potential selection bias. Having already restricted the sample to the four regions of Ethiopia where fertilizer has been available and widely used since its introduction in the late 1960s (Rashid & Negassa 2011; IFDC 2012), I am left with 1,732 households in the sample, of which 22% did not use fertilizer at all in any given year, while only 44% used fertilizer in all 3 waves. The most common reasons for not using fertilizer were its high price and lack of money, with only 4% of households reporting ignorance of its use by the third wave. This implies that households which

[11] The average number of men in each of those categories is 0.48 (20-34), 0.32 (35-49), and 0.18 (50-64).

did not use fertilizer chose not to (as opposed to being unaware of it) and are likely to be systematically different from those which did. In particular, households not using fertilizer are likely to do so either because they cannot use it profitably, or because they lack the means to purchase it. Both of these could be correlated with household composition.

To mitigate this potential selection bias, I estimate fertilizer demand conditional on it being used in a given growing season.[12] Restricting the sample accordingly allows me to isolate households for which fertilizer is profitable from those for which fertilizer is either unprofitable or too risky to use, as the latter group faces a different set of constraints. It should be noted, however, that including households which went from zero use to non-zero use in one year to the next means that the overall effect will be a combination of intensive and extensive margin effects. This will likely result in point estimates that are higher than if I were just looking at households which used fertilizer in all three survey waves, but doing so reduces the sample size too much.

With this caveat, the conditional fertilizer demand equation is similar to that for labor demand, with household composition included in the same way, and controls for household landholdings, wealth, and other observable characteristics. I again include a community-time fixed effect, which absorbs input and expected output prices, as well as other shocks which would affect fertilizer profitability. Given the nature of fertilizer acquisition—through requests made to local agricultural cooperatives, which relay these requests up the chain of government

[12] I choose this approach rather than that typically taken in the literature on fertilizer demand—a double hurdle model—because estimating conditional demand allows me to account for time-invariant household-level heterogeneity through household fixed effects. The probit estimator in the first stage of the double hurdle model requires a correlated random effects approach and the assumption that, conditional on the included covariates, household composition is uncorrelated with unobserved, time-invariant household characteristics, such as farmer skill. Using household-level fixed effects allows me to avoid making this strong assumption. Although estimating conditional fertilizer demand restricts the sample significantly and gives no insight into the participation decision, it brings with it more confidence in the consistency of the household composition coefficients.

until the AISE determines how much fertilizer to import—fertilizer access may significantly between communities and potentially over time, and this is also controlled for with the community-time fixed effect. As with labor demand, I also include a year fixed effect to control for country-level trends and household fixed effects to control for time-invariant household-level characteristics such as farmer skill. That is, I estimate:

$$\ln Z_{ijt} = \delta_0 + \sum_{n=1}^{4} \delta_1^n M_{ijt}^n + \sum_{n=1}^{4} \delta_2^n F_{ijt}^n + \delta_3 \ln X_{ijt} + \delta_4 \bar{A}_{ijt} + \eta_i + \vartheta_{jt} + \tau_t + \varepsilon_{ijt} \tag{12}$$

With the same covariates as in the labor demand equation, and where *Z* is the (log) quantity of fertilizer applied in growing season *t*. The test for the null hypothesis of separability is, again, that $\delta_1 = \delta_2 = 0$. As discussed in 2.2, there are certain scenarios in which we would expect the household's labor endowment to have a positive effect on fertilizer demand: if the household is labor-constrained and cannot hire in sufficient outside labor, its fertilizer use will increase with household labor supply. Alternatively, if households are cash-constrained and unable to access credit markets, fertilizer use will increase with income from off-farm work,[13] which is increasing in labor supply. In either of these cases, if imperfections in labor markets spill over into fertilizer demand, we would expect $\delta_1 > 0$. Depending on whether female family members supply labor, we might also expect $\delta_2 > 0$.

Due to life cycle effects and gender dynamics, households with a higher share of older males are likely wealthier than those which are younger or predominantly female. Given that fertilizer is an expensive input, it is possible that any effect of household composition and, particularly, labor endowment on fertilizer demand is due primarily to a wealth effect.

[13] Or from renting out land

Controlling for household wealth through landholdings thus helps with identification of $\delta_1$and δ_2 and provides insight as to the mechanism behind any effect.

1.5.2 Identification

Despite the extensive controls provided by the inclusion of observable household characteristics, household, community-time, and year fixed effects, there remain threats to identification. Over a long enough time-frame, household composition is likely to be endogenous. For example, if local labor markets are thin, households with large landholdings may be unable to hire in sufficient labor and will instead choose to have more children to increase their labor supply. Within the five-year panel, this is unlikely to be a source of bias, as children born after the first wave will be too young to provide any meaningful labor, so that household labor supply is quasi-fixed. Shorter-term changes, particularly migration decisions, pose a bigger problem. If households send members away, either for school, to find work, or for early marriage to relieve financial pressures (e.g., the additional labor the household member could provide on the farm does not cover their consumption needs), then household composition will be partially determined by labor demand. LaFave & Thomas (2016) deal with this problem by restricting the sample to households in which changes in composition were solely due to aging, an approach I follow here through two sets of restrictions.

I first exclude households which experienced births, deaths, and migration over the course of the sample, unless that migration was due to marriage of a household member over the national median age for marriage (16.5 years old for women and 23 years old for men (Central Statistical Agency Ethiopia 2012)) or the member who died was older than the average life expectancy of 64.5 years (World Bank 2015), which leaves 881 households. Although children born after the first survey wave will be at most age 4 by the third wave, if their birth is related to a productivity shock that could affect the household longer term, there is a potential for simultaneity bias between household size and labor demand. While it would take a rare, catastrophic event for this to be the case, the same could also be true for the death of a household member. I include households with members who married because it is plausible that societal pressures to marry by a certain age are strong enough that, for household members over that age, migration for marriage is unrelated to household labor demand.

The second sample restriction is that used by LaFave & Thomas (2016) and excludes households with any births, deaths, or migration at all over the three survey waves. That is, any changes in household composition are solely due to aging. While this approach has the advantage of identifying household composition through a strictly exogenous process, its stringency comes with a cost in sample size: of the 715 households remaining, only 472 used fertilizer in either the first or second survey waves. Small sample size aside, this is the preferred specification because of the strictly exogenous nature of the composition changes.

These sample restrictions also serve to delink changes in household composition with changes in landholdings. Under current government policy, households do not own land, per se, but are given certificates of use by the state. These certificates are *de facto* land rights and remain relatively constant over the course of the survey.[14] While there is a potential for simultaneity bias between landholdings and input demand, I assume that the transactions costs associated with acquiring or relinquishing a land certificate are such that landholdings are quasi-fixed over the

[14] Simultaneity bias between landholdings and input demand is also possible, though not likely, given the quasi-fixed nature of landholdings. More problematic for identification is if both landholdings and household composition variables changed as a result of a productivity shock. If household composition changes are due solely to aging, however, then changes in landholdings are uncorrelated, conditional on the inclusion of life cycle variables (age of household head and household wealth).

course of the survey. This assumption is backed up by the relative stability of landholdings by survey wave, as shown in table 1.2.

Table 1.2: Mean area cultivated, landholdings, and share of land planted to maize, wheat, or teff by survey wave

	Wave 1	Wave 2	Wave 3
Area cultivated (ha)	1.12^{++}	1.13^{+}	1.16
	(0.95)	(0.92)	(1.02)
Landholdings (ha)	1.07^{+++}	1.22	1.19
	(1.05)	(1.10)	(1.10)
Share of cultivated land planted to maize, wheat, or teff	0.38***	0.40	0.39
	(0.28)	(0.30)	(0.30)

Standard deviations in parentheses below. $^{+}$ Wave 2 different from wave 3 at p<0.1, $^{++}$ Wave 1 different from wave 3 at p<0.05, $^{+++}$ Wave 1 different from waves 2 and 3 at p<0.1, *** Wave 1 different from waves 2 and 3 at p<0.01.

A larger concern of simultaneity bias is that caused by including area cultivated. Alternatively, excluding cultivated area could cause omitted variable bias. The bias could arise because larger areas of land generally require greater input use, while the quantity of land cultivated may reflect other input constraints. One option in dealing with this potential source of bias is to look at intensity of input demand, so that the choice variable—area cultivated—is moved to the left-hand side of the equation. Udry (1999) and Carter & Yao (2002) take this approach. Other studies look at demand for total labor rather than intensity and simply include cultivated area as a control, under the justification that it is a relatively fixed input once the growing season begins (LaFave & Thomas 2016; Dillon & Barrett 2017). Benjamin (1992) includes harvested area in his study, while Bowlus & Sicular (2003) include it directly and then run a series of robustness checks using land endowment and grain quotas as instruments, and Dillon et al. (2017) also use landholdings as an instrument.

While neither landholdings nor cultivated area change greatly over time, as shown in table 1.2, there is a clear upward trend in the survey data. As a robustness check, I also estimate input demand per hectare of land cultivated in addition to estimating total input demand. Estimating total input demand allows me to isolate the impact of household composition on a single input—labor or fertilizer—as opposed to a ratio of inputs (labor or fertilizer per hectare cultivated. Estimating intensity of input demand, on the other hand, provides a robustness check and is in keeping with the primary focus of the intensification literature.

Another, related source of simultaneity (or omitted variable) bias is crop choice. This is an issue primarily related to fertilizer demand: although different crops have different fertilizer and labor requirements (Franke 2014), many labor activities occur regardless of crop choice (e.g., land preparation, planting, and weeding), while recommendations for fertilizer application vary widely between crops. Of the six major staple crops grown in Ethiopia, the majority of fertilizer is applied to only three: teff, wheat, and maize (IFDC 2012). It is thus plausible that substitution between staple crops occurs and that fertilizer prices affect farmers' decisions of which cereals to plant.

The literature on fertilizer generally deals with this potential simultaneity bias by restricting the sample to crops on which fertilizer is typically applied. Doing so comes at the cost of estimating farm-level fertilizer demand. Moreover, I find little evidence of substitution between staple crops, with the share of cultivated land planted to maize, wheat, or teff relatively unchanged throughout the survey waves, at 0.38 in wave 1, 0.40 in wave 2, and 0.39 in wave 3, as shown in table 1.2. As an additional robustness check, however, I take the same approach as with cultivated area and estimate fertilizer demand per hectare of maize, wheat, or teff cultivated.

1.6 Separability results

In this section, I first present results for the tests of separability in agricultural labor and fertilizer demand. I then discuss in greater detail how these results change when restricting the sample to exclude households with endogenous composition changes and what can be inferred from the fact that the point estimates do, in fact change.

1.6.1 Testing for separability in labor demand

1.6.1.1 Total labor demand

Regression results for total labor demand are shown in columns 1-3 of table 1.3. Column 1 shows results for the full sample, column 2 shows those for the sample which excludes households with births, early deaths, or migration that was not due to marriage, and column 3 shows those for the aging-only sample, the preferred specification. Under the null hypothesis of separability, the household composition variables, the β_1 and β_2 in equation (11) should not be statistically different from zero. This is not the case for total labor demand: the p-values of the tests of joint significance at the bottom of the table show that the male composition point estimates—β_1—are jointly different from zero at $p<0.1$ for all sample restrictions, and the null hypothesis of separability is rejected.[15] The female composition coefficients—the β_2—are jointly different from zero for all but the most restricted sample, in column 3.[16]

[15] This also holds for the finer categorization of household composition categories (see appendix).
[16] This is probably not driven only by endogeneity of household composition because I find that they are jointly different from zero using the finer categorization of household composition categories (see appendix). In these results, the share of females aged 20-34 has a negative effect on farm labor demand, while the other female composition groups all have a positive effect. Women aged 20-34 are of prime child-bearing age, so an increase in the share of women in this group may also reflect an increase in the number of dependents. Women of this age are also usually the ones in charge of cooking, cleaning, and caring for their children, so it is possible that they are not considered part of household farm labor supply.

Table 1.3: Household-level fixed effects determinants of labor demand by sample restrictions

	(log) Total labor demand (days)			(log) Labor days/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Share of males 12-19	0.501***	0.468*	0.430	0.299*	0.262	0.254
	(0.179)	(0.282)	(0.349)	(0.180)	(0.285)	(0.349)
Share of males 20-64	0.326	0.640	0.830	0.211	0.456	0.604
	(0.273)	(0.486)	(0.683)	(0.269)	(0.466)	(0.635)
Share of males 65+	0.021	-0.608	-0.507	0.086	-0.378	-0.485
	(0.404)	(0.619)	(0.856)	(0.405)	(0.666)	(0.905)
Share of females 12-19	0.379**	0.471*	0.380	0.088	0.035	-0.234
	(0.182)	(0.273)	(0.337)	(0.182)	(0.287)	(0.342)
Share of females 20-64	0.103	-0.165	-0.244	-0.039	-0.287	-0.606
	(0.267)	(0.448)	(0.578)	(0.266)	(0.426)	(0.535)
Share of females 65+	0.053	-0.036	-0.263	-0.007	-0.332	-0.773
	(0.409)	(0.548)	(0.698)	(0.449)	(0.589)	(0.765)
HH size (log)	-0.125	-0.637		-0.255	-0.192	
	(0.263)	(0.424)		(0.245)	(0.434)	
Landholdings (log)	0.096***	0.072***	0.072***	-0.070***	-0.067***	-0.067***
	(0.013)	(0.016)	(0.019)	(0.013)	(0.019)	(0.022)
Number of observations	5,196	2,643	2,145	5,034	2,565	2,076
Adjusted R2	0.503	0.517	0.531	0.493	0.483	0.490
p-values for F-tests of joint significance						
All male comp. vars	0.021	0.044	0.078	0.365	0.336	0.353
All female comp. vars	0.102	0.102	0.340	0.869	0.779	0.715
Prime-age adults	0.480	0.402	0.476	0.698	0.456	0.349
All HH comp (excl. HH size)	0.039	0.044	0.149	0.701	0.642	0.602
All covariates	0.000	0.000	0.005	0.000	0.023	0.026

Notes: Differences in numbers of observations due to trimming cultivated area. Share variables all refer to share of household members in that gender-age group. Share of males and females under the age of 12 dropped due to multicollinearity. Standard errors clustered at the EA level and in parentheses below. Community-time fixed effects included in all specifications. *** p<0.01, ** p<0.05, * p<0.1

It is clear that the results are not driven solely by endogenous composition changes, because they hold even among the aging-only households. In fact, the point estimates on the individual composition variables show a consistent pattern. For the share of working-age males, the point estimates increase from 0.326 to 0.640, as I first restrict the sample to exclude households with any births, early deaths, or migration not due to marriage over the average age. When I restrict the sample further to exclude households with any changes not due to aging, the point estimate increases again to 0.830.

Putting this in perspective, and using the distribution of total labor demand and household composition in the first survey wave, a one standard deviation increase in the share of working-age males[17] in a household with no migrant members would result in an increase in total labor demand equivalent to roughly 18.3% of its wave 1 standard deviation. For the full sample, which includes aging-only households as well as those with migrant members, a one standard deviation increase in the share of working-age males would only increase total labor demand by 5.4% of its standard deviation.

One way of looking at this is that the share of working-age males—the household's labor supply—appears to have an increasingly large effect on farm labor demand as the sample becomes increasingly restricted. A similar trend holds for every other adult composition group but with the opposite sign: they have a more negative effect on labor demand in the aging-only sample than in the full sample. Put together, it appears that adult household composition matters more (though with opposite effects) for households with no migrant members. This general pattern holds for labor demand per hectare cultivated and both sets of fertilizer results, and I discuss it further in section 1.6.3.

[17] Which amounts to increasing the share by approximately 75%

1.6.1.2 Demand for labor per hectare cultivated

One key threat to identification of the household composition variables was omitted variable bias caused by either excluding cultivated area from the demand equation, or simultaneity bias caused by improperly including it. Columns 4-6 of table 1.3 show the results for demand for labor per hectare cultivated, with results for the full sample in column 4, those for the sample which excludes households with births, early deaths, or migration not due to marriage in column 5, and the aging-only households in column 6. The general pattern of results is consistent with those for total labor demand, but the point estimates are not precisely estimated, and separability is not rejected.[18]

These results suggest that the total labor demand results were not driven primarily by omitted variable bias, though it is possible that omitting cultivated area from the first set of regressions biased the composition coefficients upwards. For example, as column 6 shows, the point estimate for the share of working-age males in an aging-only household on demand for labor per hectare is 0.604, compared to 0.830 for total labor demand, as shown in column 3. Put differently, a one standard deviation increase in the share of working-age males in a household with no migrant members would increase labor demand per hectare by roughly 11.6% of its standard deviation. A corresponding composition change would increase total labor demand by 18.3% of its standard deviation, as noted above.

[18] One set of coefficients is consistently significant across columns 4-6: landholdings. Labor is used less intensively on large farms—with an elasticity of demand with respect to landholdings around -0.07. Put differently, there is a strong relationship between household landholdings and the area cultivated, which is suggestive of failures or high transactions costs in land markets as well.

With no (composition) coefficients which are statistically different from zero, it is impossible to say whether household composition affects demand for labor per hectare. I cannot conclude that it does, but I cannot rule out that it does not.[19]

1.6.2 Testing for separability in conditional fertilizer demand

1.6.2.1 Total fertilizer demand

Conditional fertilizer demand results are shown in table 1.4, with total fertilizer demand in columns 1-3 and fertilizer demand per hectare cultivated in columns 4-6. As with labor demand, results for the full sample are in columns 1 and 4, those for the sample which excludes households with births, early deaths, or migration not due to marriage in columns 2 and 5, and those for the aging-only households in columns 3 and 6. Unlike labor demand, I fail to reject separability in the first two columns: the p-values of the joint tests of significance at the bottom of the table show that none of the household composition coefficients are jointly significant. For the aging-only households, however, the male composition coefficients are jointly different from zero at p=0.1, and separability in total fertilizer demand for these households is rejected at the 10% level. Neither the female composition coefficients, nor the household composition coefficients combined have a joint effect that is statistically different from zero.

Although the composition coefficients are very noisy and not individually significant, there is again a consistent increase in the point estimates for the share of working-age men as I restrict the sample. In the full sample (column 1), this coefficient is nearly zero, at 0.046. In the sample which excludes households with births, early deaths, or migration not due to marriage

[19] The results using the finer composition categories, as well as other robustness checks using the number of household members in each category (as opposed to the share) suggest that there is an effect (albeit a smaller one). When using the number of members in each category, the household composition variables have a joint effect that is significant at the 10% level. Both sets of results and other robustness checks are in the appendix.

over the average age, shown in column 2, this coefficient is 0.819. In the aging-only sample, in column 3, the coefficient rises to 1.09. Translating these point estimates into units of fertilizer, a one standard deviation increase in the share of working-age males in a household in the full sample would, all else equal, increase total conditional fertilizer use by roughly 0.9% of its wave 1 standard deviation. By comparison, total conditional fertilizer use would increase by 41.6% in the aging-only sample. As with labor demand, the share of working-age men appears to matter more in households with no migrant members.

Table 1.4: Household-level fixed effects determinants of conditional fertilizer demand by sample restrictions

	(log) Conditional fertilizer demand (kgs)			(log) kgs fertilizer/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Share of males 12-19	-0.199	0.268	-0.052	-0.240	0.387	-0.076
	(0.247)	(0.365)	(0.415)	(0.256)	(0.390)	(0.456)
Share of males 20-64	0.046	0.819	1.087	-0.107	0.727	0.768
	(0.319)	(0.514)	(0.668)	(0.321)	(0.513)	(0.681)
Share of males 65+	0.364	0.590	0.637	0.387	0.860	0.843
	(0.510)	(0.772)	(0.982)	(0.489)	(0.721)	(1.298)
Share of females 12-19	0.055	0.171	-0.101	-0.308	-0.316	-0.746*
	(0.236)	(0.344)	(0.377)	(0.248)	(0.370)	(0.409)
Share of females 20-64	-0.108	0.151	-0.290	-0.239	0.071	-0.687
	(0.348)	(0.621)	(0.716)	(0.377)	(0.651)	(0.744)
Share of females 65+	-0.368	-0.276	-0.229	-0.325	-0.248	-1.187
	(0.629)	(0.957)	(1.709)	(0.594)	(0.856)	(1.416)
HH size (log)	-0.456	0.012		-0.649**	-0.046	
	(0.300)	(0.568)		(0.269)	(0.580)	
Landholdings (log)	0.057***	0.059**	0.063**	-0.103***	-0.094***	-0.086**
	(0.020)	(0.027)	(0.027)	(0.022)	(0.032)	(0.034)
Number of observations	2,890	1,451	1,185	2,890	1,451	1,185
Adjusted R2	0.314	0.424	0.454	0.365	0.440	0.446
p-values for F-tests of joint significance						
All male comp. vars	0.522	0.429	0.087	0.437	0.537	0.470
All female comp. vars	0.877	0.907	0.981	0.666	0.741	0.319
Prime-age adults	0.917	0.257	0.208	0.817	0.314	0.250
All HH comp (excl. HH size)	0.709	0.635	0.289	0.693	0.355	0.415
All covariates	0.050	0.370	0.137	0.000	0.053	0.041

Notes: Differences in numbers of observations due to trimming cultivated area. Share variables all refer to share of household members in that gender-age group. Excludes households with zero fertilizer use. Share of males and females under the age of 12 dropped due to multicollinearity. Standard errors clustered at the EA level and in parentheses below. Community-time fixed effects included in all specifications. *** p<0.01, ** p<0.05, * p<0.1

1.6.2.2 Demand for fertilizer per hectare cultivated

Columns 4-6 of table 1.4 show the results for demand for fertilizer per hectare cultivated. As with labor demand, I am unable to reject separability: none of the household composition coefficients have a joint effect different from zero.[20] The same potential issue of omitted variable bias appears to hold here: the composition point estimates are smaller for fertilizer intensity demand compared to those for total fertilizer demand.[21] For example, the share of working-age males in an aging-only household has a point estimate of 0.768—compared to 1.09 for total fertilizer demand. That is, a one standard deviation increase in the share of working-age males in an aging-only household would only increase demand for fertilizer per hectare by 13.3% of its standard deviation—compared with the 41.6% of a standard deviation increase in total fertilizer demand from above.[22] This suggests, again, that the total demand coefficients also include, to some extent, the effect of household composition on cultivated area.

Despite the failure to reject the null hypothesis of separability—which means I cannot say anything conclusively about the effect of household composition on fertilizer demand intensity—it should be noted that, again, household composition appears to matter more in households which have no migrant members than those which do.[23] As column 4 of the same table shows, the share of working-age males has a small (and noisy) effect on fertilizer demand

[20] The share of females age 12-19 does, for households with no migrant members, but it is not entirely clear why. These results should be interpreted relative to the omitted categories—the share of males (or females) under age 12, and it is not clear why, relative to these groups, females ages 12-19 would negatively affect fertilizer demand.
[21] This is also the case when estimating fertilizer demand per hectare of maize, wheat, or teff—the crops which receive the bulk of fertilizer in Ethiopia (IFDC 2012).
[22] This is in part because of the significantly larger standard deviation of fertilizer applied/ha (86.6 compared to total fertilizer demand at 44.7).
[23] Across sample restrictions, fertilizer is also applied less intensively on large farms: the elasticity of fertilizer demand per hectare with respect to landholdings is around -0.09 across sample restrictions. As with demand for labor per hectare, this is consistent with there being frictions in land markets that prevent households from reallocating land, as would be expected from the government's policy regarding land certificates.

per hectare, with a point estimate of -0.11. For the aging-only sample, the point estimate is much higher (though imprecisely estimated), at 0.768.

This pattern holds across all the results presented in tables 1.3 and 1.4, and I discuss its implications next.

1.6.3 Differences by sample restriction

Breaking down the changes in results by sample restriction, two key patterns emerge. First, there is a general trend that the share of working-age males in the household has a larger (and positive) effect on input demand in the restricted samples than in the full sample. That is, the share of working-age males in the household has a larger and positive effect on input demand per hectare among households which had no migrant members over the course of the survey, compared to households which did. This is especially pronounced in the fertilizer demand functions. Conversely, the female composition coefficients *decrease* steadily with the sample restrictions, especially in the input intensity demand regressions. The share of females of any age has either a smaller or a more negative effect on input demand in the aging-only households, compared with the rest of the sample.

What is driving the differences in results between the full sample and restricted samples? One possibility is that household composition is endogenous and biases the estimates downwards. A related but slightly different interpretation is that households in which there was no migration, births, or deaths are systematically different from those in which there were—and the two groups are indeed different on observable characteristics and input choices, as shown in table 1A.1 of the appendix. For example, households in the most restricted sample had less land and fewer household members but a higher share of female family members than households in which there were births, deaths or migration. It is plausible that whichever mechanisms prevent the aging-only households from sending a member away for work or marriage[24] also affect their input demand decisions.

Another possibility is differences in transactions costs. de Janvry et al. (1991) suggest the presence of transactions costs which limit households' participation in markets, even if those markets are otherwise complete, and Foster & Rosenzweig (2017) show how these transactions costs could vary with farm size. Another set of literature shows how high transport costs and other market frictions can lead to misallocation of inputs, including the share of labor devoted to agriculture (Gollin & Rogerson 2013). More relevant to these households is that having a migrant member could reduce the transactions costs associated with obtaining inputs or credit or income with which to purchase inputs.

This idea is supported by work showing that there are differences in households' abilities to fully participate in markets. For example, Bowlus & Sicular (2003) reject separability in villages where there are limited employment opportunities within and immediately outside rural Chinese townships but fail to do so when there is an active labor market nearby. In a similar vein, Carter & Yao (2002) argue that not all households are prevented from participating in markets in the same way, and that this implies a need for both global and local tests of non-separability.

If households in the restricted sample face higher transactions costs, it is also likely that they participate in a narrower geographic range of markets. For example, households with a migrant member living in a nearby city may travel regularly to that city, or the migrant member may send back information about fertilizer prices or people looking for temporary work. If it is

[24] For example, low liquidity or lack of information about off-farm employment and labor markets.

the case that households in the aging-only sample participate in a narrower range of markets, they are also likely to be most affected by markets at the most localized level (i.e., in and around the village), where the households with migrant members may have the means and network connections to access markets further away. Unfortunately, it is difficult to disentangle the potential effects of statistical bias, systematic differences in households, different transactions costs, and geographic spread of market access, and I leave the question for further research.

1.6.4 Implications from separability results

While the rejection of separability in itself is insufficient to determine the cause of rejection (de Janvry et al. 1991; Carter & Yao 2002), it is clear that the household's labor endowment has a positive impact on input demand for certain types of households. As discussed in section 1.2.2, this is likely caused by a discrepancy between the household's valuation of its own on-farm labor compared with off-farm labor and hired labor. The cause of this discrepancy is less clear, and there are many possibilities.

The mechanism through which labor market imperfections could cause this wedge is described in greater detail in section 1.2.2: finding that labor-constrained households use less labor would be consistent with limited off-farm employment opportunities, low availability of hired labor, or differential search and monitoring costs, as all of these would result in households preferentially working on the farm. Identifying which constraints households face requires estimating the shadow wage relative to the market wage, as Dillon et al. (2017) do. As described earlier, labor market imperfections could spill over into fertilizer demand: given that labor is needed to apply fertilizer, then to weed plots sufficiently later in the season, it is possible that labor is a binding constraint in fertilizer application.

Binding financial constraints would also explain the fertilizer results, assuming local labor markets function relatively well. If this is the case, a household which lacks the means to purchase fertilizer could earn income from working off the farm. The potential of a household to earn off-farm income will also increase with the number of members available to work off the farm, so we would expect households with a larger labor supply to be more likely to have the means to purchase fertilizer. This is consistent with reports that fertilizer is too expensive for Ethiopian farmers to use (Croppenstedt et al. 2003) but does not explain the wedge between households' valuation of their own labor compared to that of hired laborers implied by the labor demand results.

Which—if either—of these explanations holds determines what kind of policy will be most effective in increasing input use. I explore these implications further in the next section, where I estimate labor and fertilizer demand price elasticities.

1.7 Price elasticities

My results in the preceding sections showed that separability does not hold in conditional fertilizer and agricultural labor demand. They demonstrated that problems in multiple markets limit input use and intensification. In this section, I investigate further the implications for intensification by estimating the elasticities of labor and conditional fertilizer demand with respect to the price of the other. As discussed in section 1.2, price elasticities are useful because they indicate underlying relationships and trade-offs between different inputs. I first discuss estimation of the price elasticities, then discuss the results and implications for intensification.

1.7.1 Price elasticity estimation

To estimate the price elasticities, I modify equations (11) and (12) to include a vector of input and (expected) output prices. Since output prices are unknown at the time of planting, I assume households form expectations about future prices through a naïve expectations model, so that expected output prices simplify to those realized in the previous year.

As discussed in section 1.4, price data in the survey was measured at a combination of the farm level and market level, with land rental rates and wages reported by farms who participated in those markets, and fertilizer prices collected separately in community markets. While fertilizer and cereal prices are unlikely to be affected by any individual household, it is possible that certain farmers are better at negotiating than others. If this is the case, wages and land rental rates may depend on household preferences and labor supply, or be simultaneously determined with the farm's input demand.

To mitigate this potential endogeneity, and to avoid skewing of results by outliers, I take enumeration area-level medians of all prices and move up in levels of aggregation if the values are either implausible or missing. Doing so makes the price data collinear with the community-time fixed effect initially included in equations (11) and (12). As such, I drop the community-time fixed effect and include just a year fixed effect, while recognizing that doing so is at the cost of controlling for community-level trends which could bias or reduce the precision of the estimates.[25]

[25] The results on the household characteristics variables are similar across specifications but less precise when dropping the community-time fixed effect, suggesting that bias is not a major concern. The estimates were also less precisely estimated when I included a community-time fixed effect at a higher level of aggregation, compared to dropping it altogether.

While certain community-level characteristics—such as elevation and distance to an urban center—are time-invariant and are thus absorbed in the household fixed effect, rainfall, which is likely to influence planting decisions, is not. Under the assumption that farmers form expectations about rainfall according to the same naïve expectations model as assumed for expected output prices, I include the previous year's rainfall in the modified demand equation.

$$\ln I_{ijt} = \gamma_0 + \sum_{n=1}^{4} \gamma_1^n M_{ijt}^n + \sum_{n=1}^{4} \gamma_2^n F_{ijt}^n + \gamma_3 \ln X_{ijt} + \gamma_4 \bar{A}_{ijt} + \gamma_5 p_{jt}^I + \gamma_6 p_{j,t-1}^y + \theta_{j,t-1} + \eta_i + \tau_t + \varepsilon_{ijt} \tag{13}$$

Where demand for input I, either labor or fertilizer, depends on the same variables as above but also a vector of input prices, p_{jt}^I, lagged output prices, $p_{j,t-1}^y$, lagged weather shocks, θ_{jt}, and a year fixed effect τ. Here, the coefficient of interest is γ_5. If markets are complete, we would expect γ_5 to be negative, with negative own- and cross-price elasticities of both labor and fertilizer. A negative cross-price elasticity of fertilizer with respect to wages would also be consistent with a binding labor constraint. This is because an increase in the market wage would increase the cost of hiring in laborers and would also increase the opportunity cost of family labor on the farm. On the other hand, if financial constraints are binding, then an increase in the market wage would increase the income of households selling their labor off the farm. This, in turn, could relax the binding financial constraints, and fertilizer demand would increase.

As with the tests for separability, I estimate input demand for three samples: the full sample, the sample which excludes households with migration not due to marriage, births, or early deaths, and the aging-only sample. While the coefficients of interest here are no longer the household composition variables, the results in tables 1.3 and 1.4 indicate that there are systematic differences between households with migrant members and those without. This means that the two types of households may also face different binding constraints in input use. Understanding whether they respond differently to input price changes will shed some light on this.

1.7.2 Price elasticity results

1.7.2.1 Elasticity of farm labor demand

Key price elasticity results for agricultural labor and conditional fertilizer demand are given in tables 1.5 and 1.6, respectively. As before, columns 1-3 show results for total input demand, while columns 4-6 are for demand per hectare. Across all specifications, labor demand is fairly inelastic with respect to fertilizer prices, with very noisy point estimates ranging from -0.023 to 0.081, which translates into a decrease of 3 days, or 1.9% of the wave 1 standard deviation, up to an increase of 12 days, or 7.4% of the wave 1 standard deviation. As discussed above, we would expect, if markets were complete, that labor demand would decrease with fertilizer prices, as the two are complements in production. Alternatively, as fertilizer prices increase, households could be substituting towards more labor-intensive inputs, such as manure or compost application. If this were the case, we would expect labor demand to increase with fertilizer prices. Given the size of the standard errors, which range from 0.16 to 0.27, relative to the point estimates, it seems more likely that these insignificant results are not due to low power, but rather to farm labor demand not depending on fertilizer prices, an inference I discuss in greater detail below.

Farm labor demand also has a negative elasticity with respect to market wages, as expected. The own-price elasticity appears to be somewhat smaller for the restricted sample than the full sample: column 1 of table 1.5 shows the elasticity of total labor demand with respect to wages is -0.12 for the full sample, while column 2 shows it is -0.05 for households with no births, early deaths, or migration not due to marriage, and column 3 of the same table shows it is -0.08 for households with no migrants. This translates into a decline of roughly 18 days, or 11% of a standard deviation in labor for the full sample, and roughly 11 days, or 7% of a standard deviation for the aging-only sample. In column 4, the elasticity of labor demand per hectare cultivated with respect to wages is -0.11 for the full sample, but only -0.06 for the aging-only sample (in column 6). Likewise, the elasticities are significant for the full sample—for both total labor demand and demand for labor per hectare—but not for the aging-only sample.

While these differences between samples are small, they are robust to alternative specifications and are consistent with the separability results, which suggested that households with no migrant members rely more heavily on their own labor supply. That finding indicated that aging-only households may be further constrained in labor market participation than households with migrant members—who, as evidenced by the rejection of separability in total labor demand, are also not participating fully in labor markets.[26]

[26] Also consistent with most households being autarkic with respect to labor is that local labor market participation rates are low: in the first survey wave only 15% of households in the full sample worked off the farm, while 20% hired in farm labor. The hired in rate is comparable to Bachewe et al.'s (2016) findings using other Ethiopian datasets.

Table 1.5: Key farm labor demand elasticity results

	(log) Total labor demand (days)			(log) Labor days/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Fertilizer price (ETB/kg)	0.046	0.044	0.019	-0.024	0.078	-0.010
	(0.172)	(0.240)	(0.276)	(0.162)	(0.234)	(0.273)
Wages (ETB/day)	-0.119***	-0.047	-0.077	-0.109**	-0.038	-0.061
	(0.046)	(0.062)	(0.069)	(0.045)	(0.063)	(0.072)
Land rental rate	0.020	-0.036	-0.007	0.029	-0.002	0.005
(ETB/ha/season)	(0.059)	(0.081)	(0.092)	(0.059)	(0.079)	(0.092)
Lagged cereal prices (ETB/kg)	0.430***	0.320*	0.175	0.075	-0.020	-0.156
	(0.130)	(0.179)	(0.200)	(0.125)	(0.171)	(0.198)
Lagged rainfall (mm)	-0.040	-0.293*	-0.276*	-0.180*	-0.332**	-0.290*
	(0.106)	(0.151)	(0.165)	(0.102)	(0.142)	(0.157)
Number of observations	3,464	1,762	1,430	3,356	1,710	1,384
Adjusted R2	0.037	0.039	0.033	0.008	0.007	0.001

Notes: Differences in numbers of observations due to trimming cultivated area. Standard errors clustered at the EA level and in parentheses below. All regressions estimated with household-level fixed effects and include year fixed effects. All prices are in nominal birr. All prices and rainfall are in logs. All covariates from the main specifications are also included. Labor demand for wave 1 is not included, due to the lagged variables.
*** p<0.01, ** p<0.05, * p<0.1

1.7.2.2 Elasticity of conditional fertilizer demand

Elasticity results for fertilizer demand are presented in table 1.6. As in previous tables, columns 1-3 show the results for total fertilizer demand, and demand for fertilizer per hectare cultivated is in columns 4-6. As with labor demand, the own-price elasticity is significantly lower for the restricted samples than the full sample. The magnitude of the effect drops from a statistically significant -0.42 (for total fertilizer demand, in column 1) or -0.34 (for fertilizer demand per hectare, in column 4) to less than one-fourth of its size when the sample is restricted to exclude households with migrant members.[27] That is, if the price of fertilizer doubled, households in the full sample would decrease their fertilizer by roughly 25 kilograms, or 55% of the wave 1 standard deviation, while households in the aging-only sample would only do so by one-fifth of that—5 kgs, or 10.5% of the wave 1 standard deviation. For all of the restricted samples, in columns 2, 3, 5, and 6, the effects are small and very imprecisely estimated.

This suggests that, for a given decrease in fertilizer prices, certain types of households will only respond with a marginal increase in fertilizer use. This finding is somewhat at odds with that of Dercon & Christiansen (2011), who conclude that high fertilizer prices are a primary constraint to its use in Ethiopia. On the other hand, there is evidence that fertilizer prices in Ethiopia are lower than those in neighboring countries (Jayne & Rashid 2013), and it is possible that fertilizer demand is fairly inelastic at current prices. Also consistent with my results are

[27] It is unclear what is driving these results. It does not appear to be differences in fertilizer application rates, as shown in table 1.3. While there is slightly more variation in fertilizer prices among households with migrant members, the difference does not seem large enough to drive these results. One possibility is that households with no migrant members rely more heavily on farm production for consumption and are thus less sensitive to changes in input prices than are households with alternate sources of income, namely, that from migrant members. As with the differences in separability results by sample restriction, I leave this question for further research.

those of Josephson et al. (2014), who found a negative but not statistically significant effect of fertilizer prices on fertilizer use in Ethiopia.

Interestingly, the elasticity of fertilizer demand with respect to the market wage is of roughly the same magnitude as the own-price elasticity of fertilizer demand among the restricted samples, though the effect (for all samples) is not statistically different from zero. Across all samples, the elasticity is in the 0.06-0.08 range, meaning that a doubling of the market wage would, all else equal, increase fertilizer demand by roughly 5 kilograms, or 10.5% of the wave 1 standard deviation.

With insignificant point estimates, it is impossible to draw any definitive conclusions, but a positive relationship between market wages and fertilizer demand would suggest liquidity problems that could be relaxed by household members earning income off of the farm. Although the effect is small and is not precisely estimated, it is consistent across alternative specifications, suggesting the issue may be one of power and that further disaggregation may reveal interesting patterns, a question I leave for further research.

Table 1.6: Key conditional fertilizer demand elasticity results

	(log) Conditional fertilizer demand (kgs)			(log) kgs fertilizer/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Fertilizer price (ETB/kg)	-0.417**	-0.087	-0.085	-0.341	-0.002	0.130
	(0.202)	(0.240)	(0.264)	(0.209)	(0.260)	(0.274)
Wages (ETB/day)	0.063	0.078	0.055	0.040	0.062	0.052
	(0.047)	(0.061)	(0.067)	(0.054)	(0.073)	(0.078)
Land rental rate	0.150***	0.231***	0.154*	0.189***	0.319***	0.215**
(ETB/ha/season)	(0.056)	(0.082)	(0.089)	(0.066)	(0.097)	(0.103)
Lagged cereal prices (ETB/kg)	0.360**	0.310	0.210	0.168	0.026	0.134
	(0.161)	(0.228)	(0.260)	(0.166)	(0.227)	(0.248)
Lagged rainfall (mm)	0.168	0.192	0.092	0.083	0.151	0.103
	(0.118)	(0.158)	(0.173)	(0.132)	(0.175)	(0.191)
Number of observations	2,000	1,007	822	2,000	1,007	822
Adjusted R2	0.033	0.062	0.039	0.071	0.082	0.073

Notes: Differences in numbers of observations due to trimming cultivated area. Standard errors clustered at the EA level and in parentheses below. Households with zero fertilizer use are excluded. All regressions estimated with household-level fixed effects and include year fixed effects. All prices are in nominal birr. All prices and rainfall are in logs. All covariates from the main specifications are also included. Labor demand for wave 1 is not included, due to the lagged variables. *** p<0.01, ** p<0.05, * p<0.1

1.7.3 Implications from price elasticities

Taken together, these results rule out certain explanations. First, the low own-price elasticity of farm labor demand suggests that households are not participating fully in agricultural labor markets. An increase in the market wage should increase the price of hired laborers, as well as the opportunity cost to a household of working on the farm, thereby lowering total farm labor demand. Instead, as discussed in section 1.2.2.3, there may be high search costs—both in finding off-farm employment and in hiring laborers, high monitoring costs, or other reasons that farm labor demand is relatively inelastic with respect to the market wage. These costs may be mitigated somewhat for households with members living elsewhere; though the difference in elasticities between the full sample and the restricted samples is small, further disaggregation may be needed to explore whether this is the case.

Given the low own-price elasticity of fertilizer demand for households in either of the two restricted samples, the low elasticity of labor demand with respect to fertilizer prices is not surprising: the primary mechanism through which households adjust their labor use in response to fertilizer prices is most likely through fertilizer use. If fertilizer use does not change much with fertilizer prices, neither should labor.

Relatedly, the low own-price elasticity of fertilizer demand with respect to wages is consistent with the labor own-price elasticity results, as well as with households not participating fully in agricultural labor markets. As mentioned previously, the complementarity of fertilizer and labor means that, if markets were complete, fertilizer demand would decrease with wages. The insignificant but consistently positive relationship between fertilizer use and market wages warrants further exploration to determine whether certain types of households would increase their fertilizer use as a result of market wage increases. That is, and as described in section 1.2.3, households with a relatively high labor endowment but which are liquidity-constrained may increase their fertilizer use if their off-farm income increases. Examining whether this is the case is challenging, as larger households also tend to be wealthier, but is an area for further work.

For households with no migrant members, fertilizer demand is relatively inelastic with respect to fertilizer prices. As such, solely lowering the cost of fertilizer is unlikely to significantly increase its use among these households, suggesting they face other constraints. This is potentially contradictory with the finding that fertilizer demand (weakly and noisily) increases with market wages but again highlights the need for further disaggregation and examination of whether different types of households are constrained in fertilizer use in different ways.

1.8 Conclusion

As the primary asset of the rural poor, the degree to which households can sell or substitute their own labor with that of others can directly affect their abilities to allocate resources efficiently. This is especially true for smallholders, who lack collateral or are otherwise unable to obtain credit with which to purchase inputs. In this paper, I suggest that one under-explored constraint to fertilizer use results from problems in agricultural labor markets. I build on the classic test of separability pioneered by Benjamin (1992) and use household-level panel data to test whether household composition affects both agricultural labor and conditional fertilizer demand among smallholders in Ethiopia.

In both instances, separability is rejected, and the share of working-age men in a household has a positive impact on total farm labor and total conditional fertilizer demand. In particular, a one standard deviation increase in the share of working-age males in a household with no migrant members would, all else equal, increase total labor demand by 18.3% of its wave 1 standard deviation and total conditional fertilizer demand by 41.6% of its wave 1 standard deviation. My results are robust to controlling for community-level prices and shocks, as well as the endogeneity of household composition, cultivated area, and crop choice, though I am unable to reject the null hypothesis that household composition has no effect on demand per hectare of either input.

I also estimated the price elasticities of both inputs and found that agricultural labor is relatively inelastic with respect to market wages, with an elasticity of -0.08 among households with no migrant members. This is consistent with households not participating fully in labor markets. Similarly, fertilizer demand among households with no migrant members is only weakly elastic with respect to fertilizer prices, with an elasticity of -0.09, suggesting that lowering fertilizer prices is unlikely to significantly increase fertilizer application rates among certain types of households. Taken together, these results indicate that policies which focus on increasing the functioning of agricultural and other local labor markets may indirectly increase fertilizer use, though the degree to which this would hold is difficult to determine, given that the estimated effect of wages on fertilizer demand is not statistically different from zero.

In focusing on conditional fertilizer demand, this paper examined whether problems in local labor markets affect fertilizer demand at the intensive margin. A natural follow-up question is whether this is true for the decision to use fertilizer at all. Also, while this paper noted differences in input demand separability and elasticities for households with no migrant members, compared to the pooled sample, it remains agnostic as to what drives these differences. Whether they are due to statistical bias, systematic differences between households, or because having a migrant member lowers barriers to participation in markets is a question left to further research.

Encouraging use of yield-increasing inputs such as fertilizer remains a pressing challenge to policymakers, especially in the face of rising population density. Previous work has shown that policies aimed at increasing input use must address the multifaceted constraints of smallholders. This paper suggests that improving the functioning of agricultural labor markets is a good place to start.

APPENDIX

Table 1A.1: Wave 1 summary statistics for input use and household characteristics for households included and excluded from restricted sample

	Subsample=0	Subsample=1		Subsample=0	Subsample=1
Inputs			**HH characteristics**		
Labor demand (person days)	165.0	131.9	Landholdings (ha)	1.19	0.92
	(171.6)	(149.5)		(1.10)	(0.94)
Labor days/ha cultivated	194.0	180.9	Share of males in HH	0.51	0.49
	(224.4)	(205.9)		(0.18)	(0.20)
Used fert. in first survey wave	0.52	0.51	Share of females in HH	0.49	0.51
	(0.50)	(0.5)		(0.18)	(0.20)
Hectares cultivated	1.22	1.0	Share of prime-age males	0.19	0.21
	(1.02)	(0.84)		(0.14)	(0.16)
Ha of maize, wheat, or teff	0.49	0.41	Share of prime-age females	0.21	0.23
	(0.56)	(0.51)		(0.12)	(0.15)
kg fertilizer applied	60.0	59.2	Household size	5.92	4.54
	(46.3)	(44.7)		(2.10)	(1.83)
kg fertilizer applied/ha cultivated	72.7	88.3	Asset index score	-0.25	-0.40
	(99.4)	(125.4)		(0.90)	(0.65)
kg fertilizer applied/ha of maize, wheat, or teff	423.2	821.3	Age of HH head	47.7	40.1
	(2542.3)	(5877.5)		(14.3)	(14.2)
			Male headed HH	0.84	0.84
				(0.37)	(0.37)

Standard deviations in parentheses below. Fertilizer application rates are conditional on non-zero use.

Table 1A.2: Household-level fixed effects determinants of labor demand by sample restrictions using disaggregated gender-age groups

	(log) Total labor demand (days)			(log) Labor days/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Share of males 12-19	0.502***	0.449	0.350	0.302*	0.242	0.193
	(0.179)	(0.278)	(0.346)	(0.180)	(0.284)	(0.349)
Share of males 20-34	0.411	0.649	0.738	0.329	0.502	0.570
	(0.276)	(0.493)	(0.685)	(0.271)	(0.469)	(0.627)
Share of males 35-49	0.616*	0.404	0.522	0.646*	0.504	0.574
	(0.347)	(0.577)	(0.766)	(0.344)	(0.540)	(0.689)
Share of males 50-64	0.683	1.254*	2.259**	0.446	1.123	2.007*
	(0.497)	(0.714)	(1.115)	(0.484)	(0.763)	(1.072)
Share of males 65+	0.424	-0.042	0.847	0.393	0.286	0.955
	(0.554)	(0.739)	(1.275)	(0.551)	(0.828)	(1.250)
Share of females 12-19	0.349*	0.396	0.279	0.066	-0.023	-0.308
	(0.183)	(0.272)	(0.331)	(0.185)	(0.289)	(0.336)
Share of females 20-34	0.080	-0.303	-0.381	-0.028	-0.360	-0.684
	(0.270)	(0.452)	(0.574)	(0.270)	(0.432)	(0.533)
Share of females 35-49	0.853**	0.576	0.599	0.836**	0.610	0.201
	(0.360)	(0.558)	(0.734)	(0.354)	(0.547)	(0.704)
Share of females 50-64	0.989**	1.180*	1.122	0.730*	0.802	0.275
	(0.437)	(0.624)	(0.830)	(0.439)	(0.700)	(0.941)
Share of females 65+	0.936*	1.273*	1.150	0.762	0.741	0.132
	(0.537)	(0.684)	(0.921)	(0.561)	(0.788)	(1.100)
HH size (log)	0.061	-0.523		-0.078	-0.041	
	(0.245)	(0.437)		(0.235)	(0.438)	
Landholdings (log)	0.097***	0.075***	0.075***	-0.070***	-0.064***	-0.064***
	(0.013)	(0.016)	(0.020)	(0.013)	(0.019)	(0.022)

Table 1A.2 (cont'd)

	(log) Total labor demand (days)			(log) Labor days/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Number of observations	5,196	2,643	2,145	5,034	2,565	2,076
Adjusted R2	0.505	0.520	0.535	0.494	0.485	0.492
p-values for F-tests of joint significance						
All male comp. vars	0.073	0.066	0.030	0.360	0.536	0.312
Prime-age males	0.351	0.119	0.083	0.261	0.489	0.257
All female comp. vars	0.011	0.013	0.073	0.046	0.189	0.384
Prime-age females	0.027	0.027	0.091	0.013	0.073	0.158
Prime-age adults	0.107	0.057	0.053	0.042	0.198	0.165
All HH comp (excl. HH size)	0.018	0.015	0.027	0.096	0.372	0.344
All covariates	0.000	0.000	0.001	0.000	0.028	0.042

Notes: Differences in numbers of observations due to trimming cultivated area. Share variables all refer to share of household members in that gender-age group. Share of males and females under the age of 12 dropped due to multicollinearity. Standard errors clustered at the EA level and in parentheses below. Community-time fixed effects included in all specifications. *** p<0.01, ** p<0.05, * p<0.1

Table 1A.3: Household-level fixed effects determinants of conditional fertilizer demand by sample restrictions using disaggregated gender-age groups

	(log) Conditional fertilizer demand (kgs)			(log) kgs fertilizer/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Share of males 12-19	-0.210	0.256	-0.056	-0.253	0.362	-0.072
	(0.250)	(0.368)	(0.416)	(0.258)	(0.392)	(0.453)
Share of males age 20-34	-0.019	0.710	1.047	-0.179	0.552	0.742
	(0.325)	(0.528)	(0.681)	(0.332)	(0.529)	(0.672)
Share of males age 35-49	-0.254	0.563	1.093	-0.576	0.102	0.481
	(0.439)	(0.655)	(0.784)	(0.453)	(0.700)	(0.803)
Share of males age 50-64	0.389	1.259	3.031**	-0.369	0.674	1.299
	(0.628)	(0.920)	(1.242)	(0.633)	(0.987)	(1.312)
Share of males age 65+	0.638	0.837	2.628*	0.110	0.629	1.433
	(0.684)	(0.940)	(1.494)	(0.674)	(0.979)	(1.740)
Share of females 12-19	0.047	0.171	-0.123	-0.311	-0.305	-0.746*
	(0.239)	(0.347)	(0.384)	(0.250)	(0.371)	(0.411)
Share of females 20-34	-0.159	0.164	-0.296	-0.283	0.072	-0.718
	(0.354)	(0.630)	(0.721)	(0.385)	(0.663)	(0.749)
Share of females 35-49	-0.319	-0.039	0.025	-0.684	-0.542	-0.821
	(0.462)	(0.775)	(0.885)	(0.488)	(0.817)	(0.944)
Share of females 50-64	0.123	-0.127	0.196	-0.442	-0.720	-1.215
	(0.531)	(0.845)	(1.062)	(0.564)	(0.905)	(1.149)
Share of females 65+	-0.119	-0.442	0.203	-0.558	-0.959	-1.766
	(0.721)	(1.065)	(1.928)	(0.732)	(1.060)	(1.740)
HH size (log)	-0.396	-0.042		-0.727**	-0.230	
	(0.301)	(0.585)		(0.298)	(0.593)	

Table 1A.3 (cont'd)

	(log) Conditional fertilizer demand (kgs)			(log) kgs fertilizer/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Landholdings (log)	0.057***	0.058**	0.068**	-0.103***	-0.096***	-0.085**
	(0.020)	(0.027)	(0.027)	(0.022)	(0.032)	(0.034)
Number of observations	2,890	1,451	1,185	2,890	1,451	1,185
Adjusted R2	0.315	0.423	0.455	0.366	0.440	0.445
p-values for F-tests of joint significance						
All male comp. vars	0.537	0.643	0.053	0.518	0.705	0.547
Prime-age males	0.491	0.363	0.085	0.514	0.406	0.462
All female comp. vars	0.794	0.986	0.990	0.636	0.764	0.526
Prime-age females	0.587	0.971	0.911	0.511	0.704	0.708
Prime-age adults	0.675	0.626	0.300	0.706	0.451	0.551
All HH comp (excl. HH size)	0.669	0.624	0.248	0.728	0.227	0.570
All covariates	0.070	0.424	0.122	0.000	0.024	0.061

Notes: Differences in numbers of observations due to trimming cultivated area. Share variables all refer to share of household members in that gender-age group. Excludes households with zero fertilizer use. Share of males and females under the age of 12 dropped due to multicollinearity. Standard errors clustered at the EA level and in parentheses below. Community-time fixed effects included in all specifications.
*** p<0.01, ** p<0.05, * p<0.1

Table 1A.4: Household-level fixed effects determinants of labor demand by sample restrictions using condensed gender-age groups

	(log) Total labor demand (days)			(log) Labor days/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Share of males 20+	-0.153	0.094	0.368	-0.049	0.178	0.362
	(0.208)	(0.386)	(0.530)	(0.200)	(0.370)	(0.515)
Share of females 20+	-0.335*	-0.622*	-0.651	-0.178	-0.339	-0.426
	(0.202)	(0.362)	(0.468)	(0.190)	(0.319)	(0.399)
HH size (log)	-0.160	-0.674		-0.260	-0.179	
	(0.260)	(0.430)		(0.240)	(0.428)	
Landholdings (log)	0.096***	0.071***	0.070***	-0.070***	-0.067***	-0.067***
	(0.013)	(0.016)	(0.019)	(0.013)	(0.019)	(0.022)
Number of observations	5,196	2,643	2,145	5,034	2,565	2,076
Adjusted R2	0.502	0.514	0.529	0.493	0.483	0.490
p-values for F-tests of joint significance						
All HH comp (excl. HH size)	0.180	0.229	0.370	0.617	0.539	0.504
All covariates	0.000	0.000	0.004	0.000	0.004	0.005

Notes: Differences in numbers of observations due to trimming cultivated area. Share variables all refer to share of household members in that gender-age group. Share of males and females under the age of 12 dropped due to multicollinearity. Standard errors clustered at the EA level and in parentheses below. Community-time fixed effects included in all specifications. *** p<0.01, ** p<0.05, * p<0.1

Table 1A.5: Household-level fixed effects determinants of conditional fertilizer demand by sample restrictions

	(log) Conditional fertilizer demand (kgs)			(log) kgs fertilizer/ha cultivated		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Inc. migration for marriage, deaths over 65	Aging only	Full sample	Inc. migration for marriage, deaths over 65	Aging only
Share of males 20+	0.218	0.585	1.146**	0.158	0.563	0.948*
	(0.232)	(0.364)	(0.478)	(0.243)	(0.384)	(0.540)
Share of females 20+	-0.128	-0.061	-0.186	0.062	0.252	0.006
	(0.264)	(0.516)	(0.648)	(0.299)	(0.557)	(0.709)
HH size (log)	-0.503*	-0.004		-0.618**	0.014	
	(0.298)	(0.518)		(0.258)	(0.539)	
Landholdings (log)	0.056***	0.060**	0.063**	-0.103***	-0.090***	-0.082**
	(0.020)	(0.027)	(0.028)	(0.022)	(0.032)	(0.035)
Number of observations	2,890	1,451	1,185	2,890	1,451	1,185
Adjusted R2	0.314	0.424	0.456	0.365	0.439	0.444
p-values for F-tests of joint significance						
All HH comp (excl. HH size)	0.523	0.218	0.044	0.808	0.341	0.195
All covariates	0.014	0.121	0.022	0.000	0.034	0.019

Notes: Differences in numbers of observations due to trimming cultivated area. Share variables all refer to share of household members in that gender-age group. Excludes households with zero fertilizer use. Share of males and females under the age of 12 dropped due to multicollinearity. Standard errors clustered at the EA level and in parentheses below. Community-time fixed effects included in all specifications.
*** p<0.01, ** p<0.05, * p<0.1

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2 FACTOR PRICES, MARKET IMPERFECTIONS, AND INPUT USE IN KENYA: BOSERUP RE-EXAMINED

2.1 Introduction

While Kenya is widely perceived to be a success story in increasing modern input use, it is not clear that smallholder households are adapting sufficiently to keep up with rising land pressures. A recent study in Kenya by Muyanga & Jayne (2014) showed the concerning trend of increased population density being associated with decreasing farm sizes, household income per adult equivalent, and, after a threshold of 705 persons/km^2, value of farm production per hectare. Without significant policy changes, this trend seems likely to continue, if not worsen: as shown in table 2.1, the rental price of land nearly doubled in all regions of Kenya between 2010 and 2014, with an increase from 2,471 KSH to 4,384 KSH in zones with low growing potential and 6,795 KSH to 10,522 KSH in zones with high growing potential.[28] Although agricultural daily wages also increased over the same period, the change was much more moderate: they rose from 120 KSH to 142 KSH in low potential zones and 100 to 142 in high potential zones.

Table 2.1: Median real input prices in Kenya 1997-2014

		1997	2004	2007	2010	2014
Low potential zones	Land rental rates (KSH/ha/season)	8,049	3,684	3,540	2,471	4,384
	Agricultural daily wage (KSH/day)	195	159	143	120	142
	DAP price (KSH/50 kg)	4,560	2,833	2,722	3,000	2,342
High potential zones	Land rental rates (KSH/ha/season)	12,878	9,825	8,850	6,795	10,522
	Agricultural daily wage (KSH/day)	195	149	143	100	142
	DAP price (KSH/50 kg)	4,560	2,982	2,579	2,800	2,307

Notes: All prices are in 2010 KSH. High potential zones=Western Transitional, High Potential Maize, Western Highlands, Central Highlands. Low potential zones=Coastal Lowlands, Eastern Lowlands, Western Lowlands, Marginal Rain Shadow.

[28] These prices and the wages that follow are all adjusted to 2010 KSH.

Understanding how households respond to changing factor prices is thus of utmost importance, and in this paper I test whether they adjust input use based solely on relative prices or whether this response is inhibited by other factors, including, possibly, market frictions. Using a 13-year panel of 1,208 rural households located throughout Kenya, I estimate farm- and field-level demand for inputs that increase production at the extensive and intensive margins—land and fertilizer, respectively. Following the work of Binswanger et al. (1987) and others, I examine how the inclusion of year fixed effects, district fixed effects, and household fixed effects changes own- and cross-price elasticities of farm input demand. Once controlling for secular trends with a year fixed effect and differences in local agro-ecological potential and market conditions with district fixed effects, I find that land rental rates have an effect not statistically different from zero on demand for cultivated area, a small (but marginally significant) effect on the decision to use fertilizer at the extensive margin, with an elasticity of 0.045, and a larger and significant effect on fertilizer demand at the intensive margin, with an elasticity of 0.273. Across all specifications, wage rates do not appear to have a systematic effect on demand for either input. Overall, this is evidence against the hypothesis that only relative prices matter and suggests that market frictions impede the degree to which households adapt to changing relative prices.

This study differs both methodologically and in its focus from a growing set of papers on Boserupian intensification.[29] Most recent work focuses on the first part of her hypothesis: the ramifications of rising population density. Using the same dataset, Muyanga & Jayne (2014) find a negative relationship between population density and farm size and a positive relationship between population density and agricultural intensification—but only up to 500 persons/km^2.

[29] Boserup hypothesizes that, as population density rises, relative input prices will change such that the relatively more scarce good, land, becomes more expensive relative to labor, which has become more abundant. Households will then substitute away from use of land-intensive cultivation practices in favor of those which are land-saving, such as fertilizer use.

Josephson et al. (2014) find similar patterns in Ethiopia, though without the threshold. Also in Ethiopia, Headey et al. (2014) show higher rates of use of purchased inputs and family labor in land-constrained villages. In Malawi, Ricker-Gilbert et al. (2014) find a negative relationship between population density and farm size but that population density only indirectly increases fertilizer use through its effect on landholdings, wages, and maize prices. Finally, a recent study by Binswanger-Mkhize & Savastano (2017) uses cross-sectional data from six countries in sub-Saharan Africa to show that higher population density is associated with increased fertilizer use but suggest that overall application rates are insufficient to compensate for decreased fallow periods, which they find are also associated with higher population density. In focusing solely on the second part of Boserup's hypothesis, household response to changing relative prices, this paper thus fills a key gap in the recent literature on agricultural intensification.

Another set of closely related, if mostly dated, literature uses price elasticity estimation to examine the potential welfare effects of price policy. Much of this work focuses on the effects of price policies on consumption and welfare (e.g., Deaton 1989, Deaton & Grimard 1992, Wodon & Zaman 2008, D'Souza & Jolliffe 2010) or production (e.g., Trivedi & Akayima 1992, with reviews of older work in Askari & Cummings 1976, 1977 and Bond 1983). A smaller set of papers estimate price elasticities for farm input demand. Sidhu & Baanante (1979) estimate joint profit and factor demand functions for wheat varieties in India and show, from own- and cross-price elasticities, that fertilizer demand is more responsive to changes in wheat prices than in fertilizer prices. Binswanger et al. (1987) take an approach similar to that in this paper and estimate the short-run price elasticities of farm input demand and supply in 58 countries. They find that fertilizer demand is more responsive to fertilizer prices than demand for cultivated area is to its own price but that country effects have a larger effect than any of the included prices.

On the other hand, empirical work on market frictions, imperfections, and transactions costs typically looks at their role in limiting input use, rather than in limiting changes in input use in response to price changes. For example, Duflo et al. (2011) show that a lack of commitment or savings mechanisms lower fertilizer use among smallholders in Kenya. In Ghana, Karlan et al. (2014) find that incomplete insurance markets limit agricultural investment, including the acres of land cultivated and expenditures on chemical inputs. Related work examines how varying transactions costs, which could lead to market failures, affect input use. Using the same dataset as in this study, Suri (2011) shows that heterogeneous costs and returns explain Kenyan farmers' adoption of hybrid maize seed. Also in Kenya, Alene et al. (2008) find that high transactions costs, including access to information, limit fertilizer adoption,[30] while Aggarwal et al. (2017) show that geographic remoteness is associated with lower rates of fertilizer adoption in Tanzania.

While it is commonly accepted that there are frictions in rural sub-Saharan African factor markets, there are, to my knowledge, few existing studies that explicitly examine the implications for agricultural input use. In linking the three sets of literature described in the preceding paragraphs, this paper takes a first step towards filling this gap. I first show that there is very little adjustment in the quantity of land a household cultivates in response to changes in land rental prices and wages: the elasticity of cultivated area with respect to land rental rates is -0.001, while that with respect to wages is 0.004, and neither is statistically different from zero. This finding is consistent with there being high transactions costs associated with participating in land rental markets, as found by Jin & Jayne (2013). It is also consistent with work (e.g., Jayne et al. 2014) indicating that households in densely populated rural areas are unable to easily acquire

[30] Though not a primary focus of their study, they also find that fertilizer use increases with higher levels of population pressure on land, which is consistent with the intensification literature described in the preceding paragraph.

additional arable land, which in turn implies that increasing production at the extensive margin is no longer an option for most smallholders.

Second, I show that, while fertilizer demand within a given year increases with local land rental rates, the bulk of this variation is attributable to between-district and between-household heterogeneity. When examining response within districts, the elasticity point estimates are, at best, halved from 0.373 to 0.045 for the binary decision to use nitrogen applied through inorganic fertilizer, and 0.551 to 0.273 for conditional nitrogen demand. At the plot level, and when accounting for time-invariant household characteristics with a household fixed effect, they drop further, to 0.029 for the binary use decision and 0.119 for conditional demand—the latter of which is not statistically different from zero. That is, a doubling in the cost to rent land results in households being only 4.5% more likely to use nitrogen-containing inorganic fertilizer and to apply roughly 10.5 additional kilograms of nitrogen, or 24% of the 2010 standard deviation.

Third, while data limitations prevent estimation of farm-level labor demand, I show descriptively that household sizes declined over the 13 years of the survey. This is the case both for the number of total members and when adjusting for adult equivalence. One potential explanation is that households may be adapting by sending adult members away, rather than through increasing farm production or finding local off-farm employment opportunities.

Taken together, these results indicate that households are not responding flexibly to changes in land rental rates or local wages. Instead, changes in fertilizer use appear to be primarily driven by changes fertilizer prices and year effects—the latter of which may reflect increases in fertilizer availability over time—while key drivers of changes in demand for cultivated area are less clear. This finding is in contrast with Boserup's (1965) hypothesis of how farming systems change in response to rising population density. Instead, my results suggest that smallholders do not make production decisions based solely or even mainly on relative prices, but that other factors matter too—a conclusion that is now implicitly accepted in most studies on input use and agricultural intensification in sub-Saharan Africa. This conclusion is also fairly consistent with recent empirical work testing Boserup's hypothesis. Although many of these studies find support for her hypothesis in declining land sizes and increased use of purchased inputs and family labor in response to rising population density, they also control for household characteristics and market access in estimation, an implicit acknowledgement that these characteristics do in fact matter. Similarly, Binswanger-Mkhize & Savastano (2017) find evidence of only weak intensification across six African countries, while Headey & Jayne (2014) conclude that rising population density has led to reduced fallows but only limited increases in fertilizer use and non-farm income diversification in Africa.

Finding that smallholders do not make intensification decisions based solely or even mainly on relative prices has important policy implications. It suggests that policies which focus only on relative prices—through subsidies or price supports—are unlikely to be effective in promoting intensification. Moreover, it suggests that households face other constraints to input use due to market frictions. Failing to address these constraints can lead to misallocation of inputs at the household level, which ultimately affects aggregate productivity[31] and, hence, GDP (e.g., Gollin & Udry 2017, Adamopoulos et al. 2017, Restuccia and Santaeulalia-Llopis 2017, with a review in Restuccia & Rogerson 2013). As such, reducing these frictions so that households can respond flexibly to relative price changes has potentially large implications for overall efficiency and welfare.

[31] Although Gollin & Udry (2017) show that the high estimates of productivity losses due to misallocation are in part actually due to mismeasurement and unobserved heterogeneity in land quality, they find non-trivial losses in productivity from misallocation in Ghana, Uganda, and Tanzania.

The rest of the paper proceeds as follows: the next section discusses input markets in Kenya, and section 2.3 describes the data and variable selection. Section 2.4 presents the econometric and identification strategies, section 2.5 discusses the results, and the final section concludes.

2.2 Input markets in Kenya

Input use in Kenya has been sharply increasing over the past two decades and is significantly higher than elsewhere in sub-Saharan Africa. Sheahan (2011) shows that, between the mid-1990s and 2005, fertilizer use in Kenya increased by approximately one-third and by another one-fourth between 2005 and 2010. Consistent with this story are the findings of Ariga et al. (2008) that the percentage of smallholders using fertilizer on maize jumped from 56% in 1996 to 70% in 2007, with a corresponding increase in application rates from 34 kg/acre to 45 kg/acre. This high average use has been attributed to a stable fertilizer policy market that was liberalized in the early 1990s (Ariga et al. 2006). Following the liberalization of fertilizer markets, the number of fertilizer wholesalers and retailers in rural Kenya grew rapidly, with significant investment in private fertilizer distribution networks, such that, by 2006, over 10 importers, 500 wholesalers, and 7,000 retailers were operating throughout the country (Ibid.).

There is signification geographic variation in fertilizer use, however. Obare et al. (2003) found over 90% of farmers using chemical fertilizer on maize in Nakuru, while, in Vihiga and South Nandi, Marenya & Barrett (2009) found 88% of the farmers in their study using fertilizer in 2004. In low potential zones, the percentage of households using fertilizer is much lower: in 2007, 43% of households in Eastern Lowlands, 13% in the Western Lowlands, and 16% in Marginal Rain Shadow used inorganic fertilizer (Ariga et al. 2008). Conditional fertilizer application rates, or dose rates, vary similarly. In 2007, an average ranging from 47-75 kilograms of fertilizer per acre was applied in high potential zones, compared to 16 kg/acre in Eastern Lowlands and 12 kgs/acre in Western Lowlands (Ibid.) Much of the variation in use appears to be due to variation in profitability of use due to different agro-ecological conditions (Sheahan et al. 2013).

Participation in land rental markets in Kenya has also risen over the past two decades. Jayne & Jin (2013) find an increase in the proportion of households renting in land from 18% in 1997 to 20% in 2007, and the Government of Kenya explicitly promotes the development of land rental markets (Government of Kenya 2007). Land reallocations from land rental and sales markets have been found to improve efficiency in production and equity between households (Yamano et al. 2009), and, in the case of land rentals, increase farm productivity and household income (Jin & Jayne 2013). While both land sales and rental markets are legal and active, Jin & Jayne (2013) show that land-renting households still do not use farm labor and land at economically optimal ratios—indicating the presence of high transactions costs or market imperfections—and suggest avenues to improve the functioning of land rental markets, including the removal of local restrictions.

While empirical studies on agricultural labor markets in Kenya remain limited, those elsewhere in East Africa have been shown to be incomplete. Dillon et al. (2017) provide evidence of excess supply of labor in rural areas of Malawi, Tanzania, and Uganda, and excess demand among poor households in Ethiopia, though they suggest this excess demand is primarily driven by financial market failures rather than limited supply of laborers. Consistent with these findings, Kopper (2018) shows that incomplete agricultural labor markets limit fertilizer use and the own-price elasticity of fertilizer use in Ethiopia. Greater attention is paid to household labor supply to rural off-farm markets, including studies on income diversification (e.g., Barrett et al. 2005) and migration (e.g., Hoddinott 1994). More recently, Mathenge & Tschirley (2015) show that farm households use casual agricultural labor as a short-term coping strategy in response to specific, unexpected rainfall shocks, while non-agricultural employment is primarily used as a long-term response to anticipated shocks. These results, as well as their finding that households in areas which receive less rainfall are more likely to participate in (non-agricultural) off-farm labor markets, are consistent with labor market imperfections that would result in households preferentially using their own labor on the farm.

2.3 Data and variable selection

The length of the panel used in this study provides an opportunity to examine households' response to changing relative prices over time. The 13-year panel survey of 1,260 households in rural Kenya, implemented by Egerton University and with support from Michigan State University, includes 24 districts which represent the range of agro-ecological zones (AEZs) in Kenya. The sampling frame for the first wave of the survey, in 1997, was constructed with assistance from the Kenya National Bureau of Statistics. Within the 24 districts selected, all rural divisions were matched to their respective AEZ or AEZs. Divisions from each AEZ were then selected proportional to the population across zones, and households within each selected division were then randomly chosen. The 1997 survey covered 1500 households in 109 villages. Over the next five waves of the survey—in June of 2000, 2004, 2007, and 2010—a total of 1,243 households were resurveyed, resulting in an average attrition rate between rounds of approximately 17% over all five waves. Re-interview models show that observed attrition is for the most part random, and, in other studies, attrition-corrected estimates are very close to uncorrected estimates, suggesting little attrition bias (Jin & Jayne 2013).

While the panel was conducted over five survey waves, the 2000 round did not collect data on land rental rates and is thus dropped from this study. After excluding households which cultivated under 0.1 hectares of land, I am left with a balanced panel of 1,208 households, of which 208 did not use fertilizer in any survey wave and 617 which applied nitrogen through inorganic fertilizer and 544 applied phosphorus in all 4 survey waves. 2010 summary statistics for the variables used in the analysis are presented in table 2.2.

Input use and crop choice were collected at the plot level, with detailed data on different types of fertilizer used. Although DAP and CAN are the primary types of fertilizer used on maize in Kenya, non-trivial amounts of other fertilizer types are also used. There are three main options for dealing with this: first, I can estimate demand for each fertilizer type separately, which would require accounting for substitution between types. Another option is to pool across types, or to pool basal fertilizers and top dressings. While simpler, this approach would lead to measurement error, given different prices and nutrient components. As such, I take a third approach, one often taken in the agricultural production economics literature, and estimate demand for nitrogen and phosphorus, the two primary components of the major fertilizer types used in Kenya, and the two nutrients that are widely found to be deficient in sub-Saharan Africa's soils (Stoorvogel & Smaling 1990; Sanchez et al. 1997). To do so, I compute the quantity of nitrogen or phosphorus provided by each fertilizer type, following the nutrient breakdown described in Sheahan (2011).[32] I then pool across fertilizer types to obtain farm-level demand for both nutrients, hereafter referred to as fertilizer demand for simplicity.

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[32] For simplicity, I refer to the amount of elemental phosphorus from the compound P_2O_5 in inorganic fertilizers as phosphorus.

Table 2.2: Summary statistics of variables used in regressions (2010 values)

	N	Mean	SD
Household-level input demand			
Cultivated area (ha)	1,208	1.25	1.62
Area planted to maize (ha)	1,018	0.69	0.95
Maize area/total cultivated area	1,018	0.54	0.25
Number of fields	1,208	3.62	1.82
Number of maize fields	1,018	1.43	0.66
kg N applied	885	38.3	43.8
kg N/ha	885	34.6	28.4
kg P applied	842	27.2	30.8
kg P/ha	842	25.3	23.6
kg N applied to maize	727	21.9	30.0
kg N applied to maize/ha of maize	694	34.8	24.9
kg P applied to maize	656	14.9	17.1
kg P applied to maize/ha of maize	656	23.0	12.2
Field-level input demand and area controls			
Field size (ha)	3,291	0.43	0.69
Maize field size (ha)	1,250	0.56	0.75
kg N applied	1,536	16.87	21.01
kg N/ha	1,536	44.79	45.04
kg P applied	1,395	11.59	12.15
kg P/ha	1,395	33.86	39.83
kg N applied to maize	836	21.46	31.36
kg N applied to maize/ha of maize	836	36.72	25.97
kg P applied to maize	794	14.03	18.22
kg P applied to maize/ha of maize	794	24.29	13.17
Prices			
Land rental rates (KSH/ha/season)	1,208	5,753.7	3,045.4
Agricultural daily wage (KSH/day)	1,208	123.7	37.2
Nitrogen price (KSH/kg N)	1,208	247.3	67.6
Phosphorus price (KSH/kg P)	1,208	273.4	45.3
Hybrid maize seed price (KSH/kg)	1,208	133.5	21.6
Expected maize prices (KSH/kg)	1,208	24.5	3.5

Notes: Fertilizer application rates exclude zeros. Prices are all in 2010 KSH. Expected maize prices are those for the previous main harvest, adjusted to 2010 KSH.

Given the prominence of maize as the staple food crop and as the crop which receives the majority of fertilizer in Kenya (Ariga et al. 2008), I estimate both total fertilizer demand and demand for fertilizer applied to maize. Following Sheahan (2011), in estimating demand for fertilizer applied to maize, I restrict the sample to fields on which maize is the main crop, which means excluding fields on which more than six other crops were grown as well as those on which cash crops (tea, cotton, rice, sisal, and pyrethrum) were grown alongside maize. Similarly, in estimating demand for cultivated land, I look at three different outcomes: total cultivated area, maize area, and maize area as a fraction of cultivated area, where maize fields are as previously defined. Defining the dependent variables accordingly provides perspective on overall response to changes in prices, as well as potential shifts towards or away from planting maize. As with fertilizer demand, I aggregate field-level crop and area data up to the farm level.

Estimating demand for inputs that increase production at the intensive margin (fertilizer) and extensive margin (land) helps paint a complete story of how households respond to changing input prices. Missing from this story is labor demand. Unfortunately, while data on fertilizer use and plot size was collected for all cultivated land, households were only asked about labor used on the household's largest maize field. As such, I cannot estimate farm-level labor demand, nor can I determine whether changes in labor demand on the largest maize plot are due to changing relative prices or to substitution to other plots. Instead, I examine how household composition, particularly the share of working-age adults, changes over the four survey waves. Although I cannot determine causality with this descriptive approach, household labor supply has been found to be highly correlated with farm labor use elsewhere in rural sub-Saharan Africa (e.g., Dillon & Barrett 2017; Kopper 2018). As such, descriptive evidence on changes in household labor supply will give some indication of how farm labor demand may be changing. Moreover, my approach of using household composition is consistent with that taken by Muyanga & Jayne (2014), who use adult equivalents as a proxy for labor supply, using this same dataset.

The price data come from two sources. Land rental rates, agricultural daily wages, improved maize seed prices, and fertilizer prices by type were all collected at the household level in the Tegemeo survey. In contrast with many other agricultural household surveys, households were asked about the going price for these inputs in their area, as compared to a unit value approach, where the price is determined from the household's expenditures on a given quantity of the input. I take village-level medians of each price, moving up to the next level of aggregation where the resulting price is either unobserved or implausible. This approach has the added benefit of making price plausibly exogenous to a given household and ensures results are not driven by outliers or household-specific recall errors. Given that demand for nitrogen (phosphorus) likely depends on the price of nitrogen (phosphorus), as opposed to that for any given fertilizer type, I compute community-level median prices of nitrogen and phosphorus. To do so, I weight the price of each type of fertilizer by the community-level share of nitrogen (phosphorus) that comes from each type. As with the other prices, I begin at the village level and move up in levels of aggregation when values are missing or implausible.

While the Tegemeo data includes maize prices for each year of the survey, these prices are unknown at the time of planting. Instead, I use maize price data provided by the Famine Early Warning Systems Network (FEWSNET), which collects monthly maize prices at several major markets across Kenya. Although matching this data to villages likely obscures variation in farm-gate prices, I control for this variation in estimation, as discussed in section 2.4 below. Rainfall is similarly unknown, for the most part, at the time of planting. Where others (e.g., Sheahan 2011) have used rainfall stress, the fraction of 20 day periods with rainfall below 40 mm, as their preferred measure of climatic factors, this measure is not available for the year preceding the first survey wave (the 1996-1997 growing season). In the interest of preserving the 13-year panel, I control for rainfall in other ways, as discussed in greater detail in the following section.

Finally, much of Kenya has one main growing season each year. Four agro-ecological zones—Eastern Lowlands, Central Highlands, Western Highlands, and Western Lowlands—have two seasons. Given that the bulk of production occurs during the main growing season in these areas, I exclude the short-rain season from analysis.

2.4 Econometric strategy

In this section I present a framework of farm input demand under non-separability and discuss the strategy to identify households' response to changing land prices and wages.

2.4.1 Farm input demand under non-separability

There are a number of mechanisms by which relative prices may change over time, two of which I discuss here. From Boserup's (1965) work and the induced innovation hypothesis (Hayami & Ruttan 1971), an increase in population density is expected to result in an increase in the price of the relatively more scarce good—in this case, land—and a decrease in the price of the relatively less scarce good, labor.[33] Alternatively, improved market access may reduce the costs associated with participating in factor markets. For example, better roads will make it cheaper to transport goods such as fertilizer out to rural retailers, thereby lowering fertilizer prices in remote areas. At the same time, improved market access may increase demand for arable land, which is now accessible to people outside the immediate vicinity, and facilitate out-migration, thereby affecting local labor markets and, hence, local wages.

As a result of changes in relative prices, profit-maximizing farm households are expected to adjust their input use. In particular, if land prices increase relative to other input prices, we

[33] A useful decomposition of the expected changes resulting from rising population density is provided by Headey & Jayne (2014).

would expect a decrease in their use of land-intensive cultivation practices, such as fallowing, in favor of those which are land-saving, such as fertilizer use.[34] Whether this holds in practice is the focus of this paper.

Given evidence of market imperfections throughout rural sub-Saharan Africa (e.g., Dillon & Barrett 2017, Kopper 2018), I assume that smallholders in Kenya solve a non-separable problem. That is, farm production decisions do not just depend on technical relationships and prices, but also on household characteristics, endowments, and preferences. Following the work of Singh et al. (1986) and others, this implies that demand for cultivated land *A*, fertilizer *Z*, and farm labor *L* can be given by:

$$A^* = A^*(w, r, p^z, p^H, E(p^y), \theta;\ \varphi) \tag{1}$$
$$Z^* = Z^*(w, r, p^z, p^H, E(p^y), \theta;\ \varphi) \tag{2}$$
$$L^* = L^*(w, r, p^z, p^H, E(p^y), \theta;\ \varphi) \tag{3}$$

As in standard input demand functions, they depend on input prices—the market wage *w*, the price of land *r*, fertilizer prices p^z, and, given complementarity between fertilizer use and hybrid maize seed, as well as the high proportion of households in Kenya which use the two in tandem (Sheahan et al. 2013), hybrid maize seed prices p^H. They also depend on output (maize) prices, which are unknown at the time of planting and are thus included as expected maize prices, $E(p^y)$. Agro-climatic conditions, such as rainfall, elevation, and temperature shocks also affect the expected profitability of input use and, hence, input demand, and these are included as θ.

[34] That is, households will maintain the equality of the price and marginal product ratios, or $\frac{r}{p^Z} = \frac{MPP_A}{MPP_Z}$, where *r* denotes the land rental rate, p^z the price of fertilizer, and MPP_A and MPP_Z the marginal physical products of land and fertilizer, respectively. An increase in *r* will lead to a reduction in *A* (and, thus, an increase in MPP_A). Alternatively, households could increase their use of fertilizer, resulting in a decrease in MPP_Z.

Under non-separability, households may make production decisions according to risk preferences, household assets, farmer skill, household labor supply, and other characteristics. For example, if there are high transactions costs associated with buying, selling, or renting land, the quantity of land a household cultivates is largely determined by its landholdings. Similarly, if there is a low availability of hired labor or outside employment, or if there are different returns to hired versus family labor, household labor supply will be highly correlated with farm labor use. Without well-functioning credit or financial markets, some households may face liquidity or financial constraints in purchasing fertilizer, and without complete insurance markets, risk averse households may be less inclined to purchase inputs whose expected profitability depend heavily on rainfall and other exogenous shocks. These and other household characteristics which could affect input demand, including farmer skill, are included as φ.[35]

2.4.2 Estimating household level input demand

This section describes the strategy to identify whether households adjust their production decisions at the extensive and intensive margins in response to changing land prices and wages. Taking a linear approximation of equations 1 and 2,[36] but first assuming that markets are complete and that farm households solve a separable problem, where only prices and marginal products matter, I estimate the following:

$$\ln(A_{ijt}) = \beta_1 \ln(r_{jt}) + \beta_2 \ln(w_{jt}) + \beta_3 \ln(p_{jt}^{z}) + \beta_4 \ln(p_{jt}^{H}) + \beta_5 \ln(p_{j,t-1}^{y}) + \varepsilon_{ijt} \qquad (4)$$

$$\ln(Z_{ijt}) = \gamma_1 \ln(r_{jt}) + \gamma_2 \ln(w_{jt}) + \gamma_3 \ln(p_{jt}^{z}) + \gamma_4 \ln(p_{jt}^{H}) + \gamma_5 \ln(p_{j,t-1}^{y}) + \varepsilon_{ijt} \qquad (5)$$

[35] Given that households for the most part cultivate the same fields year after year, φ also accounts to some extent for differences in land quality and other characteristics that could affect profitability of input use.
[36] Due to data limitations, I do not estimate farm labor demand directly. Instead, I provide descriptive evidence on how household composition changes over the four survey waves.

As above, A denotes demand for cultivated land—total cultivated area, area planted to maize, and maize area as a fraction of total cultivated area. Z again denotes fertilizer demand, where Z is given as demand for either nitrogen or phosphorus, and, as described in section 2.3, is included in several ways: the binary decision to use nitrogen (or phosphorus), total demand for both nutrients (individually), the quantity applied to maize, the dosage rate (kilograms of either nutrient per hectare cultivated), and the dosage rate on maize. Also as above, r denotes land rental rates, w agricultural daily wages, p^z fertilizer prices, and p^H hybrid maize seed prices—all of which are in 2010 KSH. Given that farmers do not know crop prices at planting time, I assume that they form expectations about the current season's prices through a naïve expectations model and include the previous year's crop prices as p^y. I first estimate farm-level input demand for household i in village j and year t without any additional controls.

β_1, β_2, γ_1, and γ_2 are the primary coefficients of interest.[37] If households change their input use based solely on relative input and (expected) output prices, then these coefficients should not change when household characteristics are included in the input demand functions. Put differently, household characteristics should have no effect on farm input use if markets are complete. Moreover, if only relative prices matter, and following Boserup's hypothesis, we would expect fertilizer demand to increase as land prices rise, or $\gamma_1 > 0$. Given the complementarity of labor and fertilizer in the production process, fertilizer demand should decrease with wages, or $\gamma_2 < 0$. Similarly, given low rates of mechanization, cultivation is labor-intensive, so we would expect $\beta_2 < 0$, while the own-price elasticity of land should be negative, or $\beta_1 < 0$. The own-price elasticity of fertilizer demand, γ_3, is also of interest, as it indicates

[37] It is well-documented that a decrease in fertilizer prices over the same period in this study led to a sharp increase in fertilizer use (e.g., Sheahan et al. 2016), and in this paper I restrict my attention to the relative prices most likely to be affected by changes in population density.

whether households respond flexibly to changes in fertilizer prices, or whether there are other factors, such as transactions costs, that affect households' response. Here, the magnitude of γ_3 is more informative than the sign, as we would expect $\gamma_3 < 0$ in any instance.

Even if markets are complete, input use will likely depend on local growing conditions and other factors that affect profitability through technical relationships. In the next set of regressions, I thus control for aggregate trends, one of which is the rapid increase in the number of fertilizer sellers throughout Kenya (Sheahan et al. 2016), with a year fixed effect, τ. The third set of regressions adds a district-level fixed effect, υ, which controls for agro-climatic characteristics, such as rainfall, and other local characteristics that could affect the expected profitability of input use, including elevation.[38] Putting this together, I estimate:

$$\ln(A_{ijt}) = \beta'_1 \ln(r_{jt}) + \beta'_2 \ln(w_{jt}) + \beta'_3 \ln(p^z_{jt}) + \beta'_4 \ln(p^H_{jt}) + \beta'_5 \ln(p^y_{j,t-1}) + \upsilon_d + \tau_t + \varepsilon_{ijt} \quad (6)$$

$$\ln(Z_{ijt}) = \gamma'_1 \ln(r_{jt}) + \gamma'_2 \ln(w_{jt}) + \gamma'_3 \ln(p^z_{jt}) + \gamma'_4 \ln(p^H_{jt}) + \gamma'_5 \ln(p^y_{j,t-1}) + \upsilon_d + \tau_t + \varepsilon_{ijt} \quad (7)$$

The construction of land rental rates and agricultural daily wages—community-level[39] median values of the prices reported by farmers as either the rate to rent one acre of quality land for one season or the local agricultural daily wage—means that these prices are plausibly exogenous to each household. Another advantage is that these prices are reported as local prices by households, rather than imputed by dividing expenditure on an input by the quantity purchased. The latter approach, as shown by Deaton (1988) will ultimately result in estimates of

[38] While a village-level fixed effect would better control for these unobserved factors, including differences in land quality, it is highly collinear with the village level prices (land, wages, and fertilizer prices). Similarly, soil data was collected at the village level, but there is little variation within districts, so I exclude it from the analysis.
[39] As mentioned in section 2.3, these are for the most part village-level medians, but are medians taken at higher levels of aggregation when the village-level median is either missing or implausible.

price elasticities for a given (unobserved) level of quality of a good. This unobserved quality component would present challenges to identification of price elasticities that are mitigated by the phrasing of the survey questions.

That said, there is likely significant variation in what constitutes "good quality" land between villages. The district-level fixed effect, υ, controls for this variation to some degree, and is more straightforward than McKelvey's (2011) rather data-intensive method to disentangle demand for quality from that for quantity. With υ and τ, the coefficients of interest—β'_1, β'_2, γ'_1, γ'_2, and γ'_3—are identified by within-year, within-district variation. While there is considerably more variation between years and districts, leading to potential concerns of low statistical power, the main priority is identification of these coefficients. As the district fixed effect means that equations (6) and (7) are less likely to suffer from omitted variable bias, they are the preferred specifications for household-level input demand.

2.4.3 Estimating field-level fertilizer demand

The year fixed effect and district effect control for yearly, country-level trends and local characteristics that could affect the expected profitability of cultivating land or using fertilizer, even when markets are complete. They do not, however, control for idiosyncratic differences between households that would be expected to affect input use if markets are not complete, as shown in equations (1)-(3). In order to test whether β_1, β_2, γ_1, γ_2, and γ_3 change once controlling for household characteristics, I estimate fertilizer demand at the field level, which increases the frequency at which a given household is represented in a given year and provides sufficient variation to use household fixed effects.[40]

[40] Given that the decision to increase production at the extensive margin, by increasing the area of land cultivated, is a farm-level decision, I focus on fertilizer demand for this part of the analysis.

First, for the sake of comparison with the farm-level fertilizer demand results, and due to the fact that most households only cultivated one or two maize fields in a given year, I re-estimate equation (7) using field-level fertilizer demand, Z_{hijt}, where *h* denotes the field cultivated by household *i* in village *j* and year *t*, and everything on the right hand side is the same.

Next, I estimate the following:

$$\ln(Z_{hijt}) = \gamma''_1 \ln(r_{jt}) + \gamma''_2 \ln(w_{jt}) + \gamma''_3 \ln(p^z_{jt}) + \gamma''_4 \ln(p^H_{jt}) + \gamma''_5 \ln(p^y_{j,t-1}) + \eta_i + \tau_t + \varepsilon_{hijt} \tag{8}$$

Equation (8) models demand for nitrogen or phosphorus on field h and includes a household fixed effect, η, as well as the year fixed effect, τ. γ''_1, γ''_2, and γ''_3 are again the coefficients of interest. If households are basing their input use decisions based solely on prices and marginal products, price changes, which in theory have the same effect on profitability of input use on all of a household's fields, should result in input demand changes that are the same across a household's fields. If this is the case, then the field-level estimates should be roughly equal to the household-level estimates, or $\gamma''_1 \approx \gamma'_1$, $\gamma''_2 \approx \gamma'_2$, and $\gamma''_3 \approx \gamma'_3$.

Including the household-level fixed effect has several advantages. It controls for unobserved household characteristics that may affect fertilizer demand, including risk aversion—since fertilizer is an inherently risky input—and farmer skill, since better skilled farmers may cultivate more land and use more inputs. Under the assumption that these unobserved characteristics do not vary greatly over the 13-year panel, η absorbs these and other time-invariant characteristics that may inform production decisions. For the most part, it also absorbs observable characteristics that do not vary much over time, such as landholdings or land quality, which could affect the profitability of fertilizer use. Similarly, if households face liquidity constraints or difficulty in obtaining credit to buy inputs, household assets, which are largely comprised of landholdings (Burke et al. 2007), could affect a household's access to fertilizer.

Equation (8) does not, however, control for field characteristics that would affect fertilizer profitability through technical relationships, or characteristics which may not affect profitability but do affect the farmer's decision as to where to apply fertilizer. Without field-level soil data, I cannot control directly for soil fertility, while certain characteristics such as elevation are also absorbed by the household fixed effect. Given evidence on a relationship between plot size and input application rates,[41] I control for plot size in two ways. First, as previously mentioned, I estimate not just total fertilizer application rates, but dosage rates—kilograms of nitrogen or phosphorus applied per hectare. Second, I include plot size in equation (9) as a, which also indicates whether any relationship between plot size and fertilizer application rates is linear. That is, I estimate:

$$\ln(Z_{hijt}) = \gamma'''_1 \ln(r_{jt}) + \gamma'''_2 \ln(w_{jt}) + \gamma'''_3 \ln(p^z_{jt}) + \gamma'''_4 \ln(p^H_{jt}) + \gamma'''_5 \ln(p^y_{j,t-1}) + \gamma'''_6 \ln(a_{hijt}) + \eta_i + \varepsilon_{hijt} \qquad (9)$$

As above, if only relative prices matter, then we would expect $\gamma'''_1 \approx \gamma'_1$, $\gamma'''_2 \approx \gamma'_2$, and $\gamma'''_3 \approx \gamma'_3$. Given the potential importance of controlling for secular trends with a year fixed effect, as compared to plot size being the sole available plot characteristic, equation (8) is the preferred specification for field-level fertilizer demand.

2.4.4 Identification

A key challenge in identifying γ_1 and γ_2 in their various forms is that, as has been shown by others using this same dataset (e.g., Sheahan et al. 2013), fertilizer is used by farmers who can do

[41] See, e.g., Sheahan & Barrett (2017) for recent, cross-country evidence.

so profitably, and failing to account for selection into fertilizer use will result in biased estimates. There are two main options in dealing with selection bias. The first approach, one which is often taken by other studies on fertilizer demand, is a double hurdle model, where the binary decision of whether to use fertilizer is estimated via probit in the first stage and the inverse Mills ratio from that estimation included in the second stage, which models the quantity of fertilizer demanded. Using fixed effects to control for the unobserved heterogeneity described above, such as farmer skill or risk aversion, with a probit, will result in the incidental parameters problem. As such, I take the second approach and model the two decisions separately.

First, I estimate the binary use decision using a linear probability model (LPM), which allows me to use fixed effects at varying levels.[42] Second, and separately, I estimate conditional fertilizer demand, again using an LPM. Doing so has the disadvantages of not allowing me to examine the two decisions together and restricting the sample size (and, relatedly, external validity) when estimating demand at the intensive margin. On the other hand, examining conditional fertilizer demand on its own fully separates households which can use fertilizer profitably from those which either cannot or for other reasons—perhaps limited access—choose not to. Similarly, the household fixed effect I include in estimating field-level input demand assists with identification of γ_1 and γ_2 without making overly strong assumptions about whether I have included all of the household and local characteristics which may affect fertilizer use. Without field-level soil characteristics or a field-level panel, it also controls, as much as possible, for differences in soil quality between households that would affect the expected profitability of input use. For example, wealthier households may cultivate better land, which generally increases both the expected profitability of cultivating land and of using fertilizer. While the

[42] Angrist & Pischke (2009) argue that LPMs provide a reasonable approximation, a result I confirm empirically (results available by request).

household fixed effect will not account for differences in soil fertility between plots cultivated by the same household, it will account for differences between households.

A second challenge is that fertilizer use is heavily dependent on crop choice, with maize receiving the bulk of fertilizer in Kenya (Ariga et al. 2006). Crop choice, in turn, may be influenced by fertilizer price, if farmers shift away from planting maize in response to high fertilizer prices. If this is the case, the simultaneity of these decisions will bias estimates downward.

Given the importance of maize as the staple food in Kenya, it is not likely that farmers are adjusting the quantity of maize they plant in response to changing fertilizer prices; instead, it is possible that farmers simply use less fertilizer if they cannot afford it and either apply fertilizer more intensively to maize or apply it to more crops if fertilizer prices decrease. As shown in table 2.3, both the share of land planted to maize and total maize acreage change somewhat over the course of the survey, though there is no clear trend: the share of land planted to maize declines after 1997 but remains fairly steady from 2004-2007, while total maize acreage increases from 1997 to 2004 and decreases from 2004 to 2010, with a large drop between 2007 and 2010. Real fertilizer prices, shown in table 2.1, declined between 1997 and 2007 and rose again in 2010. As such, it is not immediately obvious that farmers are determining how much area to devote to maize according to fertilizer prices.

Moreover, estimating demand for land planted to maize tests formally whether farmers adjust either the total land planted to maize or the share of land planted to maize in response to changing fertilizer prices. Similarly, estimating demand for fertilizer applied to maize accounts for this potential simultaneity bias indirectly.

A related problem arises with cultivated area, which could depend on land rental rates and other prices. If households decrease the area of land they cultivate as a result of rising land prices, then fertilizer demand may decrease as a result, and the coefficient on land rental rates will again be biased downward. As with crop choice, I can test directly the extent to which demand for cultivated area depends on input and expected output prices, and estimating demand for fertilizer applied per hectare accounts for this potential bias indirectly.

Table 2.3: Mean fertilizer application rates and cultivated area by agro-ecological potential 1997-2010

		1997	2004	2007	2010
Low potential zones	kg N/ha	1.8	2	3.8	4.6
	kg N/ha on maize	0.7	2.1	3	5.9
	kg P/ha	1.0	1.0	1.6	2.6
	kg P/ha on maize	0.5	1.2	1.9	3.6
	Cultivated area (ha)	1.1	1.5	1.3	1.0
	# households	387			
High potential zones	kg N/ha	26.9	35.6	37.5	35.1
	kg N/ha on maize	19.2	28.7	31.4	32.3
	kg P/ha	21.1	26	27.9	24.7
	kg P/ha on maize	15.6	19.2	19.8	20.2
	Cultivated area (ha)	1.6	1.5	1.5	1.3
	# households	821			

High potential zones=Western Transitional, High Potential Maize, Western Highlands, Central Highlands. Low potential zones=Coastal Lowlands, Eastern Lowlands, Western Lowlands, Marginal Rain Shadow. Kg N/ha on maize=kg N applied to maize fields/ha of maize (and similarly for P).

2.5 Results and discussion

In this section, I first describe the individual regression results and then discuss their overarching implications.

2.5.1 Demand for land

Determinants of demand for land, i.e., production at the extensive margin, are presented in table 2.4. Columns 1, 4, and 7 show the pooled OLS results with no year or district fixed effect for total cultivated area, area planted to maize, and area planted to maize as a fraction of total cultivated area, respectively. Columns 2, 5, and 8 include a year fixed effect, and columns 3, 6, and 9 include both a year fixed effect and a district fixed effect. Total cultivated area is fairly unresponsive to changes in land rental rates (β_1 from above). As shown in columns 1-3, the point estimates are just around zero, and I am unable to reject, for any of the three columns, that land rental rates have no effect on the quantity of land a household cultivates. This is not particularly surprising, given that there is no statistically significant difference in the average hectares of land households cultivate between 1997 and 2007, as shown in table 2.3, though there is a statistically significant decline (from 1.4 hectares to 1.25 hectares) between 2007 and 2010.

Moving to columns 4, 5, 7, and 8, the area planted to maize does decrease with land rental rates, with β_1, the elasticity, ranging from -0.134 (as in column 7) to -0.156 (as in column 5). This effect disappears with the inclusion of the district fixed effect, however, and in columns 6 and 9 I am again unable to reject the null hypothesis that $\beta_1 = 0$, or that land rental rates have no effect on the quantity of land planted to maize—either total maize area, or as a fraction of total cultivated area.

There are multiple possible reasons for the change in β_1 with or without a district fixed effect, and the two main explanations highlight the tradeoffs in whether the district fixed effect is included. First, there is less variation in land prices within districts than between districts, so the small and insignificant point estimates when including a district fixed effect could be due primarily to low statistical power, which is an argument in favor of using just a year fixed effect. On the other hand, and as mentioned in section 2.4.2, it is likely that land prices also reflect the quality of land. While the land prices used in this analysis come from households' reports of the cost to rent an acre of "good quality" land for one season, what constitutes "good" land is subjective and probably varies considerably by location. The district fixed effect controls for this unobserved variation in land quality, as well as other characteristics of local markets and growing conditions (assuming they are relatively time invariant) as much as possible, given that a fixed effect at a lower level proved to be collinear with prices. As such, the results in columns 1, 2, 4, 5, 7, and 8 are likely to be biased, as they do not account for these differences in unobserved land quality and other market and growing conditions. In all likelihood, the reduction in the point estimates when including a district fixed effect is due to a combination of the two. That said, the results for the preferred specification, in columns 3, 6, and 9 suggest that, within districts and years, households do not adjust cultivation at the extensive margin, either in total area or in maize area, as a result of changes in land prices.[43] This, in turn, suggests that households' participation in land markets is not responding flexibly to land rental prices, at least in the short run.

[43] These results are somewhat inconsistent with those of Muyanga & Jayne (2014), who found that an increase by 1,000 KSH in the land rental rate would decrease cultivated area by 2.5% but, again, the focus of their study was on population density.

Turning to elasticity of demand for land with respect to the market wage, β_2 is again statistically indistinguishable from zero for any specification, except for demand for total cultivated area using year fixed effects, which is only marginally significant. Since cultivating land requires labor, we would expect, if markets were complete, that $\beta_2 < 0$, or that demand for land would decrease with an increase in wages. Finding that it does not suggests that households are not participating actively in local labor markets, which is consistent with markets not being complete. This is perhaps unsurprising, given evidence of incomplete labor markets and a heavy reliance on family labor supply for farm production activities elsewhere in East Africa (Dillon et al. 2017).

Finally, as mentioned in section 2.4.4, bias resulting from the simultaneity of crop choice and fertilizer use decisions, as well as the simultaneity of cultivated area and fertilizer use, was a concern for the fertilizer demand equations. Table 2.4 shows that the area planted to maize—either total area or as a share of total area—seems to increase with fertilizer prices, or $\beta_3 > 0$. This is surprising, given that fertilizer is primarily applied to maize in Kenya; we would expect maize area, if anything, to decrease with a rise in fertilizer prices. This surprising sign could be due to unobserved district-level heterogeneity—perhaps an increase in fertilizer prices reflects an overall cost in consumption goods that is not captured by the prices included in equation (4), which induces households to rely more heavily on maize production for consumption purposes—because the inclusion of the district fixed effect, as in columns 6 and 9, the effect nearly disappears. Coupled with the counterintuitive sign of β_1 for area planted to maize, it seems likely that the exclusion of district fixed effects may have biased the elasticities reported in columns 4, 5, 7 and 8.

Table 2.4: Demand for cultivated land

	Cultivated area (ha)			Maize area (ha)		
	(1)	(2)	(3)	(4)	(5)	(6)
Land rental rates (KSH/ha/season)	-0.036	-0.037	-0.001	-0.143**	-0.156**	0.030
	(0.054)	(0.062)	(0.045)	(0.072)	(0.077)	(0.065)
Ag. daily wage (KSH/day)	0.137	0.199*	0.004	0.075	0.142	-0.037
	(0.092)	(0.108)	(0.091)	(0.110)	(0.120)	(0.098)
Nitrogen price (KSH/kg N)	0.012	0.175*	-0.127**	0.132	0.297***	-0.018
	(0.067)	(0.098)	(0.054)	(0.087)	(0.106)	(0.055)
Hybrid maize seed (KSH/kg)	0.029	-0.490	-0.095	-0.005	-0.884**	-0.602**
	(0.077)	(0.300)	(0.212)	(0.103)	(0.364)	(0.266)
Maize prices (KSH/kg)	-0.737***	-0.839***	-0.192*	-1.235***	-1.339***	-0.025
	(0.186)	(0.223)	(0.110)	(0.225)	(0.271)	(0.141)
Year=2004		0.329***	0.037		0.357***	0.054
		(0.081)	(0.044)		(0.092)	(0.056)
Year=2007		0.025	-0.109		-0.152	-0.266**
		(0.148)	(0.093)		(0.153)	(0.105)
Year=2010		-0.154	-0.228		-0.424	-0.574***
		(0.236)	(0.164)		(0.277)	(0.196)
Constant	1.670**	3.487*	1.861	3.304***	7.218***	3.096**
	(0.816)	(2.052)	(1.415)	(0.955)	(2.315)	(1.434)
Unit of observation	Household	Household	Household	Household	Household	Household
Year fixed effect?	No	Yes	Yes	No	Yes	Yes
District fixed effect?	No	No	Yes	No	No	Yes
# obs	4,832	4,832	4,832	4,181	4,181	4,181
Adjusted R2	0.023	0.037	0.202	0.049	0.072	0.292

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.4: Demand for cultivated land (cont'd)

	Maize area/total cult. area (ha)		
	(7)	(8)	(9)
Land rental rates (KSH/ha/season)	-0.134***	-0.152***	0.037
	(0.044)	(0.049)	(0.048)
Ag. daily wage (KSH/day)	-0.047	-0.069	-0.006
	(0.082)	(0.086)	(0.090)
Nitrogen price (KSH/kg N)	0.211***	0.190***	0.078*
	(0.060)	(0.063)	(0.047)
Hybrid maize seed (KSH/kg)	-0.023	-0.366**	-0.409**
	(0.061)	(0.177)	(0.163)
Maize prices (KSH/kg)	-0.582***	-0.623***	0.187*
	(0.165)	(0.192)	(0.103)
Year=2004		0.001	-0.038
		(0.062)	(0.049)
Year=2007		-0.236***	-0.188**
		(0.074)	(0.079)
Year=2010		-0.282**	-0.314**
		(0.135)	(0.128)
Constant	1.413**	3.884***	0.523
	(0.698)	(1.189)	(1.102)
Unit of observation	Household	Household	Household
Year fixed effect?	No	Yes	Yes
District fixed effect?	No	No	Yes
# obs	4,181	4,181	4,181
Adjusted R2	0.043	0.050	0.216

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

2.5.2 Demand for fertilizer at the extensive margin

Tables 2.5 and 2.6 show the results for the binary decision of whether to use nitrogen or phosphorus, respectively. For both nutrients, I estimate farm-level demand, shown in columns 1-3, field-level demand, shown in columns 4-6, and field-level demand for maize fields only, shown in columns 7-9. Beginning with farm-level demand, without any fixed effects (column 1 of both tables), the decision of whether to use either nutrient is positive and fairly elastic with respect to land rental rates: γ_1 is 0.331 for nitrogen and 0.310 for phosphorus, and both are statistically different from zero at the 1% level. The inclusion of a year fixed effect increases these point estimates slightly and also reflects the upward trend in households using either nutrient: for phosphorus use, each year indicator variable is positive and significant, and they increase with each year from the base year of 1997, while for nitrogen use there is a similar upward trend, though only 2010 is statistically different from zero. As mentioned earlier, the year fixed effect controls for secular trends that are plausibly exogenous to an individual household and thus result in elasticities that are more precise and less likely to suffer from omitted variable bias than those when the year fixed effect is excluded.

When looking at within-district, within-year effects in the preferred specification, however, γ'_1 drops dramatically, to 0.045 for nitrogen use and 0.037 for phosphorus use, both of which are only marginally significant. Practically speaking, this means that a doubling of land rental rates, as was the case between 2010 and 2014, would make households only 4.5% more likely to apply nitrogen-containing fertilizers and 3.7% more likely to use phosphorus-containing fertilizers. Interestingly, γ'_3, the own-price elasticity of nitrogen demand at the extensive margin is of a similar magnitude, though it is the opposite sign. With an elasticity of -0.047, a doubling in the reported price of nitrogen would only decrease households' propensity to apply nitrogen-containing fertilizers by 4.7%. This low elasticity is discussed further below.

As when estimating demand for cultivated area, the district fixed effect absorbs district-level characteristics that may affect the expected profitability of fertilizer use, such as growing potential, and its inclusion increases the precision of the point estimates. Unfortunately, the district fixed effect also absorbs variation in prices. It seems unlikely that lack of variation is the only reason for the decrease in elasticities with the inclusion of a district fixed effect, however, because the same pattern holds for fertilizer prices. While there is relatively little variation in land rental rates within districts and years, there is considerably more variation in fertilizer prices within districts and years, and it is unlikely that such a substantial decrease in point estimates is primarily attributable to a lack of variation.

Estimating the fertilizer use decision at the plot level means that each household has, on average, 3.6 observations (plots) per year, and that household fixed effects can be used. This helps with identification of the elasticity point estimates, as the fixed effect controls for differences between households in land quality, growing conditions, household characteristics that may affect the expected profitability of fertilizer use such as farmer skill, and costs associated with obtaining fertilizer, all averaged over time.

On the other hand, estimating the decision to use fertilizer at the plot level has the disadvantage of not accounting for substitution across plots: a plot not receiving fertilizer in a given year does not necessarily mean that the household did not use any fertilizer in that year. Moreover, with plot size as the only available plot characteristic (since soil type, elevation, and drainage are measured at the village level), it is difficult to determine why a given plot may receive fertilizer in a given year while another may not.

As mentioned in the preceding paragraphs, without controlling for household characteristics and differences in land quality or transport costs, household-level nitrogen demand at the extensive margin is affected slightly by land rental rates, with an elasticity of 0.045, as shown in column 3 of table 2.5. Once controlling for these household characteristics, a household's decision of whether to use fertilizer on a given plot depends only marginally, if at all, on land rental rates. For nitrogen demand, and with a district and year fixed effect, as in column 4, the elasticity is 0.037 and is marginally significant. For the preferred plot-level specification, with household and year fixed effects as in column 5, the elasticity is again marginally significant, and $\gamma''_3 = 0.029$. With household fixed effects and when controlling for plot size, as in column 6, the elasticity is even smaller—$\gamma'''_3 = 0.015$—and is not statistically different from zero. On maize plots, the effect of land rental rates on the household's decision to use nitrogen or phosphorus is not statistically different from zero; the point estimates are both very small and very imprecisely estimated. This suggests that households respond to increases in land prices by increasing use of fertilizer on non-maize fields.

The low elasticity with respect to land rental rates makes sense. If households are profit maximizers, then they are applying fertilizer where it is most profitable to do so, and this profitability is also correlated with land quality. While land rental rates are, as discussed in section 2.4.2, probably also a reflection of local land quality, they are measured at the village level and thus do not pick up on differences in land quality within households. Even if households maximize utility, not profits, which is the assumption of equations (1)-(3), then the village-level prices used are at too high a level to pick up the variation in plot characteristics that are most likely the determinants of a household's decision to use fertilizer on one plot versus

Table 2.5: Demand for nitrogen at the extensive margin

	All plots					
	(1)	(2)	(3)	(4)	(5)	(6)
Land rental rates (KSH/ha/season)	0.331***	0.373***	0.045**	0.037*	0.029*	0.015
	(0.041)	(0.038)	(0.020)	(0.019)	(0.017)	(0.016)
Ag. daily wage (KSH/day)	-0.120**	-0.141**	-0.050	-0.031	0.025	-0.042*
	(0.056)	(0.056)	(0.034)	(0.043)	(0.030)	(0.023)
Nitrogen price (KSH/kg N)	-0.366***	-0.354***	-0.047*	-0.028	-0.037*	-0.092***
	(0.046)	(0.058)	(0.024)	(0.018)	(0.020)	(0.020)
Hybrid maize seed (KSH/kg)	-0.073*	0.297	0.130	0.005	-0.034	-0.042**
	(0.042)	(0.215)	(0.099)	(0.078)	(0.076)	(0.021)
Maize prices (KSH/kg)	0.090	-0.072	0.067	0.138***	0.173***	0.110***
	(0.101)	(0.136)	(0.069)	(0.052)	(0.053)	(0.037)
Plot area (ha)				0.074***		0.098***
				(0.011)		(0.012)
Year=2004		0.079	0.093***	0.075***	0.063***	
		(0.052)	(0.027)	(0.025)	(0.024)	
Year=2007		0.102	0.164***	0.120***	0.120***	
		(0.087)	(0.048)	(0.044)	(0.038)	
Year=2010		0.363**	0.210**	0.105	0.076	
		(0.171)	(0.083)	(0.068)	(0.064)	
Constant	0.519	-1.415	-0.747	-0.364	0.293	1.390***
	(0.423)	(1.119)	(0.629)	(0.535)	(0.469)	(0.169)
Unit of observation	Household	Household	Household	Plot	Plot	Plot
Year fixed effect?	No	Yes	Yes	Yes	Yes	No
District fixed effect?	No	No	Yes	Yes	No	No
Household fixed effect?	No	No	No	No	Yes	Yes
# obs	4,832	4,832	4,832	13,870	13,870	13,870
Adjusted R2	0.221	0.232	0.517	0.232	0.282	0.305

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.5: Demand for nitrogen at the extensive margin (cont'd)

	Maize		
	(7)	(8)	(9)
Land rental rates (KSH/ha/season)	0.025	-0.019	-0.036
	(0.023)	(0.026)	(0.026)
Ag. daily wage (KSH/day)	0.018	0.066*	-0.036
	(0.041)	(0.040)	(0.035)
Nitrogen price (KSH/kg N)	-0.039	-0.011	-0.078***
	(0.027)	(0.034)	(0.032)
Hybrid maize seed (KSH/kg)	0.004	0.084	-0.038
	(0.102)	(0.120)	(0.029)
Maize prices (KSH/kg)	0.195**	0.165**	0.101**
	(0.075)	(0.081)	(0.054)
Plot area (ha)	-0.020		-0.001
	(0.015)		(0.014)
Year=2004	0.103***	0.108***	
	(0.028)	(0.031)	
Year=2007	0.161***	0.211***	
	(0.048)	(0.055)	
Year=2010	0.143*	0.211**	
	(0.082)	(0.095)	
Constant	-0.708	-0.153	1.844***
	(0.635)	(0.674)	(0.302)
Unit of observation	Plot	Plot	Plot
Year fixed effect?	Yes	Yes	No
District fixed effect?	Yes	No	No
Household fixed effect?	No	Yes	Yes
# obs	5,165	5,165	5,165
Adjusted R2	0.491	0.609	0.603

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.6: Demand for phosphorus at the extensive margin

	All plots					
	(1)	(2)	(3)	(4)	(5)	(6)
Land rental rates (KSH/ha/season)	0.310***	0.375***	0.032*	0.033*	0.024	0.014
	(0.044)	(0.040)	(0.018)	(0.018)	(0.017)	(0.015)
Ag. daily wage (KSH/day)	-0.108	-0.100	-0.021	-0.037	0.009	-0.023
	(0.069)	(0.070)	(0.037)	(0.040)	(0.032)	(0.031)
Phosphorus price (KSH/kg P)	-0.322***	-0.103	0.004	0.086*	0.059*	-0.134***
	(0.058)	(0.098)	(0.052)	(0.049)	(0.037)	(0.035)
Hybrid maize seed (KSH/kg)	-0.127***	0.155	0.133	0.034	0.026	-0.033
	(0.043)	(0.234)	(0.102)	(0.074)	(0.076)	(0.021)
Maize prices (KSH/kg)	0.026	-0.123	0.181***	0.161***	0.190***	0.112***
	(0.125)	(0.158)	(0.068)	(0.046)	(0.049)	(0.037)
Plot area (ha)				0.063***		0.087***
				(0.010)		(0.011)
Year=2004		0.276***	0.120***	0.133***	0.112***	
		(0.063)	(0.035)	(0.029)	(0.029)	
Year=2007		0.278**	0.227***	0.203***	0.198***	
		(0.122)	(0.057)	(0.047)	(0.046)	
Year=2010		0.483**	0.247***	0.187***	0.166**	
		(0.208)	(0.083)	(0.067)	(0.069)	
Constant	0.881	-2.439	-1.532**	-1.279**	-0.549*	1.502***
	(0.535)	(1.534)	(0.675)	(0.568)	(0.559)	(0.174)
Unit of observation	Household	Household	Household	Plot	Plot	Plot
Year fixed effect?	No	Yes	Yes	Yes	Yes	No
District fixed effect?	No	No	Yes	Yes	No	No
Household fixed effect?	No	No	No	No	Yes	Yes
# obs	4,832	4,832	4,832	13,870	13,870	13,870
Adjusted R2	0.163	0.183	0.515	0.226	0.275	0.292

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.6: Demand for phosphorus at the extensive margin (cont'd)

	Maize plots		
	(7)	(8)	(9)
Land rental rates (KSH/ha/season)	0.033	-0.000	-0.012
	(0.022)	(0.021)	(0.021)
Ag. daily wage (KSH/day)	-0.047	0.015	-0.034
	(0.047)	(0.040)	(0.040)
Phosphorus price (KSH/kg P)	0.130**	0.135***	-0.119***
	(0.059)	(0.054)	(0.048)
Hybrid maize seed (KSH/kg)	0.064	0.179*	-0.039
	(0.098)	(0.107)	(0.028)
Maize prices (KSH/kg)	0.184***	0.168***	0.096*
	(0.064)	(0.071)	(0.055)
Plot area (ha)	-0.030**		-0.012
	(0.015)		(0.015)
Year=2004	0.175***	0.173***	
	(0.038)	(0.042)	
Year=2007	0.267***	0.322***	
	(0.054)	(0.062)	
Year=2010	0.263***	0.355***	
	(0.084)	(0.094)	
Constant	-1.826***	-1.487***	1.883***
	(0.627)	(0.688)	(0.290)
Unit of observation	Plot	Plot	Plot
Year fixed effect?	Yes	No	Yes
District fixed effect?	Yes	No	No
Household fixed effect?	No	Yes	Yes
# obs	5,165	5,165	5,165
Adjusted R2	0.453	0.578	0.571

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

another. Consistent with this interpretation is the fact that households are more likely to use fertilizer the larger the plot, which may reflect the fixed cost of transporting fertilizer out to the plot or possibly land quality. With plot-size elasticities ranging from 7.4% to 9.8% for nitrogen use (depending on the inclusion of a year fixed effect) and 6.3% to 8.7% for phosphorus use (again depending on the inclusion of a year fixed effect) the differences are statistically significant, if not particularly large. Households appear to be less likely to use phosphorus on larger maize plots, but this effect is not statistically different from zero with the exclusion of the year fixed effect.

Given the labor requirements of using fertilizer, we would expect households to be less likely to use fertilizer with an increase in market wages, or $\gamma_2 < 0$, and this is the case for the farm-level decision to use nitrogen—until accounting for district- or household-level characteristics with the appropriate fixed effects. With the inclusion of either set of fixed effects, market wages have an effect on the binary fertilizer use decision that is statistically indistinguishable from zero for all but two specifications.[44] This suggests that farm labor demand does not respond to changes in the market wage, possibly due to a reliance on family labor supply or reciprocal labor, or to transactions costs that impede the price signal. Alternatively, the cost of labor relative to other inputs may be so low that it is not a binding constraint in fertilizer use.

Finally, demand for nitrogen at the household level and at the extensive margin decreases with an increase in the price of nitrogen, and γ_3 is fairly large, at -0.354 when including a year fixed effect, as in column 2. With the inclusion of a district fixed effect, and for all specifications

[44] The exceptions being field-level nitrogen use using household fixed effects and controlling for plot size (column 6) of table 2.5, and field-level nitrogen use on maize plots only using household and year fixed effects (column 8). In both instances, the point estimates are small (-0.042 and 0.066, respectively), are marginally significant, and are of opposite signs.

at the plot level, γ'_3 in its various forms is small, ranging from a statistically insignificant -0.11 to a highly significant -0.092. This suggests that households apply fertilizer to more plots as fertilizer prices decrease, which is fairly intuitive, as a decrease in fertilizer prices increases the expected profitability of using fertilizer on any plot. The relatively small magnitudes would be consistent with either substitution effects (for example, households do not apply fertilizer to all plots as fertilizer prices decrease, but also apply fertilizer more intensively to some plots), or the presence of transport or other costs that affect the cost of using fertilizer beyond its market price. For demand for phosphorus at the extensive margin, the field-level own-price elasticities in some specifications are, puzzlingly, positive. There is no clear pattern indicating why this might be the case, and these point estimates are not stable, so it is difficult to conclude much from these estimates.

Taken together, these results indicate that, like the decision to adjust the area of land cultivated, the decision to use fertilizer is not primarily driven by input prices. Instead, the largest coefficients, once including district or household fixed effects, are on the year indicator variables. At the household level, with the inclusion of district fixed effects, these coefficients increase steadily over time.[45] This indicates that increases in fertilizer use at the extensive margin is primarily driven by aggregate trends that are not captured in the included input and expected output prices. As suggested by Sheahan et al. (2016), one possibility is the rapid increase in fertilizer sellers across Kenya, which led to lower transport and other transactions costs associated with purchasing fertilizer. Given that the fertilizer prices used in this analysis were calculated from households' reports of local prices, we would expect that they include the costs of transporting fertilizer out to the point of sale, but not from the point of sale to the household. It

[45] Without the district fixed effect, the increases are less steady, suggesting that there was variation between districts in the overall trend of increased fertilizer use at the extensive margin over time.

is possible (and consistent with the findings of Sheahan et al. 2016) that a decline in this latter cost is an important driver of increases in fertilizer use at the extensive margin.

2.5.3 Demand for fertilizer at the intensive margin

The same pattern of results also holds for conditional fertilizer use, as shown in tables 2.7-2.10 for nitrogen use, nitrogen use on maize, phosphorus use, and phosphorus use on maize, respectively. In tables 2.7 and 2.9, columns 1-3 show results for farm-level demand for kilograms of either nutrient, while column 4 is at the plot level. Columns 5-7 show farm-level demand for kilograms of nutrient per hectare cultivated—the dosage rate—while columns 8-10 give results for field-level dosage rates. The same set of results for nitrogen and phosphorus applied to maize only are in tables 2.8 and 2.10, respectively.

Across all four tables, the elasticity of fertilizer demand with respect to land rental rates, γ_1, declines sharply with the inclusion of district-level fixed effects (γ'_1), in columns 3, 7, and 8, and with household fixed effects, γ''_1 and γ'''_1, in columns 4, 9, and 10. Using nitrogen dosage rates as the outcome of interest, it is most straightforward to compare columns 6-9. The elasticity of nitrogen applied per hectare with respect to land prices drops from 0.647 with just the inclusion of a year fixed effect, in column 6, to 0.249 with the inclusion of district fixed effects, the preferred household-level specification, in column 7—a decline of 61.5%, or from 78.8% to 30.3% of the 2010 standard deviation. This is consistent with the earlier results suggesting that the inclusion of the district fixed effect reduced potential bias arising from differences in land quality, markets, and growing conditions at the district level, though, as before, the district fixed effect also reduces the variation in village-level prices.

At the plot level and using district fixed effects, as in column 8, the elasticity drops further, to 0.157, and with the inclusion of household fixed effects, the preferred plot-level specification, γ''_1 is 0.056 and is not statistically different from zero. Households seem to increase their overall fertilizer use and application rates with an increase in land rental rates, but they do not do so on all plots—otherwise $\gamma'''_1 > 0$. More specifically, they appear to increase fertilizer use on non-maize plots more than on maize plots—as the corresponding $\gamma_1 - \gamma'''_1$ are smaller for maize fields than non-maize fields, a pattern that holds for phosphorus demand too. Given how the conditional fertilizer use sample is defined, where households that switch into using fertilizer in a given year are included in the sample, this is also probably picking up effects at the extensive margin. As discussed in section 2.5.2, increases in land rental rates appear to increase fertilizer use at the extensive margin on non-maize plots, but not on maize plots. As such, it is not surprising that the land rental elasticities are larger for all plots than for maize plots. It is also possible that bias from crop choice is the source of the smaller maize field elasticities, and I discuss this in greater detail below.

Turning to the elasticity of conditional fertilizer demand with respect to market wages, the pattern of results is somewhat less consistent. Demand for nitrogen on all plots does not appear to depend on the market wage. Demand for phosphorus on all plots *increases* with the market wage, except with the inclusion of the household fixed effect, at which point the effect is not statistically different from zero. Demand for both nutrients applied to maize decreases (for most specifications) with the market wage, again until the household fixed effect is included. As such, and as with demand for fertilizer at the extensive margin and demand for land, it is difficult to determine whether fertilizer demand is responsive to changes in the local wage. That said, the overall inconsistency in the sign of the coefficients is consistent with other work using this same dataset (albeit different methods): Muyanga & Jayne (2014) find that fertilizer demand (measured through expenditures) is negatively affected by the market wage, while Sheahan et al. (2016) find an effect not statistically different from zero.

Finally, as we would expect, $\gamma_3 < 0$ for the most part—key exceptions being in column 10 of table 2.7, highlighting the importance of the year fixed effect, and for demand for nitrogen applied to maize (though not dosage rates on maize). Consistent with earlier results, the magnitude of γ_3 decreases with the addition of various fixed effects (from, for example, -0.756 with a year fixed effect, to -0.408 with a district fixed effect, to -0.266 with household and year fixed effects). As with demand for fertilizer at the extensive margin, γ''_3 is still statistically different from zero, which makes sense: a decrease in the cost of fertilizer will increase its expected profitability of use at both the extensive and intensive margins on all plots. Or, conversely, a doubling of the price of nitrogen will decrease households' application rates across all plots by about 40.8%—14.1 kg N/ha, or 49.7% of the 2010 standard deviation. At the plot level, application rates will decrease by 26.6%, or 11.9 kg N/ha, which is 26.4% of the 2010 standard deviation.

While the same caveats regarding tradeoffs between loss of variation and identification hold here, columns 8 and 9 of tables 2.7 and 2.8 show something new. At the plot level, γ''_3 does not change much when including a district fixed effect versus a household fixed effect (though the year fixed effect seems to matter). This suggests that omitted variable bias from local differences in land quality, transport costs, and household characteristics is, at least for field-level nitrogen demand at the intensive margin, fairly small.

Table 2.7: Demand for nitrogen at the intensive margin (all plots)

	kg N			
	(1)	(2)	(3)	(4)
Land rental rates (KSH/ha/season)	0.645***	0.551***	0.273***	0.119
	(0.106)	(0.114)	(0.070)	(0.087)
Ag. daily wage (KSH/day)	0.190	0.267	0.318**	-0.064
	(0.181)	(0.193)	(0.159)	(0.159)
Nitrogen price (KSH/kg N)	-0.660***	-0.443***	-0.536***	-0.319***
	(0.113)	(0.160)	(0.128)	(0.102)
Hybrid maize seed (KSH/kg)	-0.471***	-1.932***	0.337	1.002***
	(0.125)	(0.444)	(0.360)	(0.280)
Maize prices (KSH/kg)	-0.253	-0.287	0.541**	0.212
	(0.289)	(0.354)	(0.242)	(0.243)
Plot area (ha)				
Year=2004		0.353**	0.056	-0.369***
		(0.138)	(0.085)	(0.102)
Year=2007		-0.382	0.323*	0.170
		(0.233)	(0.170)	(0.145)
Year=2010		-0.888**	0.401	0.604**
		(0.391)	(0.309)	(0.258)
Constant	3.333**	10.690***	-3.121	-2.196*
	(1.370)	(3.348)	(2.151)	(1.873)
Unit of observation	Household	Household	Household	Plot
Year fixed effect?	No	Yes	Yes	Yes
District fixed effect?	No	No	Yes	No
Household fixed effect?	No	No	No	Yes
# obs	3,339	3,339	3,339	6,108
Adjusted R2	0.111	0.131	0.309	0.258

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.7: Demand for nitrogen at the intensive margin (all plots) (cont'd)

	kg N/ha					
	(5)	(6)	(7)	(8)	(9)	(10)
Land rental rates (KSH/ha/season)	0.709***	0.647***	0.249***	0.157**	0.056	0.070
	(0.097)	(0.104)	(0.066)	(0.063)	(0.066)	(0.065)
Ag. daily wage (KSH/day)	0.104	0.115	0.192	-0.215*	-0.044	-0.123
	(0.164)	(0.167)	(0.129)	(0.109)	(0.142)	(0.145)
Nitrogen price (KSH/kg N)	-0.758***	-0.756***	-0.408***	-0.299***	-0.266***	-0.097
	(0.103)	(0.148)	(0.104)	(0.101)	(0.091)	(0.093)
Hybrid maize seed (KSH/kg)	-0.464***	-1.129***	0.689**	0.460	0.965***	-0.242***
	(0.126)	(0.346)	(0.303)	(0.319)	(0.277)	(0.080)
Maize prices (KSH/kg)	0.590**	0.658**	0.481*	0.307	0.296	0.349**
	(0.238)	(0.307)	(0.250)	(0.197)	(0.210)	(0.183)
Plot area (ha)				-0.014		0.052
				(0.033)		(0.037)
Year=2004		-0.022	0.076	-0.176*	-0.143	
		(0.126)	(0.090)	(0.094)	(0.096)	
Year=2007		-0.319**	0.505***	0.061	0.343***	
		(0.157)	(0.145)	(0.156)	(0.140)	
Year=2010		-0.556*	0.813***	0.352	0.799***	
		(0.283)	(0.258)	(0.284)	(0.246)	
Constant	1.083	5.130**	-4.959***	-0.473	-1.481	4.330***
	(1.115)	(2.245)	(1.818)	(2.070)	(1.827)	(0.915)
Unit of observation	Household	Household	Household	Plot	Plot	Plot
Year fixed effect?	No	Yes	Yes	Yes	Yes	No
District fixed effect?	No	No	Yes	Yes	No	No
Household fixed effect?	No	No	No	No	Yes	Yes
# obs	3,339	3,339	3,339	6,108	6,108	6,108
Adjusted R2	0.177	0.180	0.357	0.169	0.275	0.271

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.8: Demand for nitrogen applied to maize at the intensive margin (maize plots only)

	kg N			
	(1)	(2)	(3)	(4)
Land rental rates (KSH/ha/season)	0.299***	0.288***	0.127*	0.008
	(0.091)	(0.103)	(0.065)	(0.079)
Ag. daily wage (KSH/day)	-0.469***	-0.411***	-0.163	0.076
	(0.154)	(0.154)	(0.162)	(0.189)
Nitrogen price (KSH/kg N)	-0.021	0.254*	-0.148	-0.226*
	(0.136)	(0.143)	(0.104)	(0.143)
Hybrid maize seed (KSH/kg)	-0.396***	-1.816***	-0.293	1.509***
	(0.116)	(0.600)	(0.490)	(0.397)
Maize prices (KSH/kg)	-1.585***	-2.025***	0.619**	0.657**
	(0.312)	(0.362)	(0.247)	(0.336)
Plot area (ha)				
Year=2004		0.670***	-0.035	-0.271**
		(0.122)	(0.102)	(0.132)
Year=2007		-0.413	-0.091	0.543***
		(0.295)	(0.212)	(0.184)
Year=2010		-0.602	-0.198	1.128***
		(0.519)	(0.401)	(0.334)
Constant	9.178***	16.437***	1.722	-6.455***
	(1.431)	(4.136)	(2.520)	(2.407)
Unit of observation	Household	Household	Household	Plot
Year fixed effect?	No	Yes	Yes	Yes
District fixed effect?	No	No	Yes	No
Household fixed effect?	No	No	No	Yes
# obs	2,769	2,769	2,769	3,212
Adjusted R2	0.113	0.168	0.379	0.594

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.8: Demand for nitrogen applied to maize at the intensive margin (maize plots only) (cont'd)

	kg N/ha of maize					
	(5)	(6)	(7)	(8)	(9)	(10)
Land rental rates (KSH/ha/season)	0.441***	0.434***	0.096*	0.087	-0.016	0.001
	(0.077)	(0.092)	(0.050)	(0.057)	(0.070)	(0.072)
Ag. daily wage (KSH/day)	-0.421***	-0.437***	-0.194	-0.166	0.075	-0.129
	(0.110)	(0.114)	(0.133)	(0.147)	(0.166)	(0.196)
Nitrogen price (KSH/kg N)	-0.313***	-0.315***	-0.244**	-0.243**	-0.213**	-0.123
	(0.076)	(0.105)	(0.098)	(0.099)	(0.102)	(0.121)
Hybrid maize seed (KSH/kg)	-0.358***	-0.861***	0.364	0.315	1.327***	-0.292***
	(0.091)	(0.323)	(0.393)	(0.426)	(0.387)	(0.090)
Maize prices (KSH/kg)	-0.144	-0.356*	0.677***	0.776***	0.623**	0.632***
	(0.193)	(0.212)	(0.217)	(0.229)	(0.283)	(0.240)
Plot area (ha)				-0.039		-0.125***
				(0.035)		(0.044)
Year=2004		0.123	-0.082	-0.087	0.006	
		(0.097)	(0.087)	(0.098)	(0.114)	
Year=2007		-0.347**	0.164	0.186	0.730***	
		(0.167)	(0.185)	(0.201)	(0.179)	
Year=2010		-0.313	0.384	0.394	1.291***	
		(0.297)	(0.334)	(0.361)	(0.309)	
Constant	5.343***	8.955***	-1.051	-1.361	-4.675**	4.594***
	(0.884)	(2.408)	(2.323)	(2.528)	(2.439)	(1.101)
Unit of observation	Household	Household	Household	Plot	Plot	Plot
Year fixed effect?	No	Yes	Yes	Yes	Yes	No
District fixed effect?	No	No	Yes	Yes	No	No
Household fixed effect?	No	No	No	No	Yes	Yes
# obs	2,634	2,634	2,634	3,212	3,212	3,212
Adjusted R2	0.116	0.132	0.268	0.283	0.500	0.492

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.9: Demand for phosphorus at the intensive margin (all plots)

	kg P			
	(1)	(2)	(3)	(4)
Land rental rates (KSH/ha/season)	0.600***	0.365***	0.141**	0.027
	(0.103)	(0.095)	(0.062)	(0.072)
Ag. daily wage (KSH/day)	0.411**	0.433***	0.350**	-0.188
	(0.159)	(0.156)	(0.160)	(0.146)
Phosphorus price (KSH/kg P)	-1.261***	-1.678***	-1.164***	-0.243
	(0.127)	(0.246)	(0.272)	(0.227)
Hybrid maize seed (KSH/kg)	-0.197*	-2.255***	-0.705**	0.408
	(0.113)	(0.392)	(0.339)	(0.276)
Maize prices (KSH/kg)	-0.479*	-0.335	0.426*	0.193
	(0.280)	(0.348)	(0.219)	(0.224)
Plot area (ha)				
Year=2004		-0.309*	-0.300**	-0.474***
		(0.162)	(0.125)	(0.113)
Year=2007		-1.319***	-0.520**	-0.174
		(0.212)	(0.214)	(0.172)
Year=2010		-2.005***	-0.874***	-0.073
		(0.304)	(0.310)	(0.269)
Constant	5.176***	21.002***	8.108***	2.011
	(1.279)	(2.784)	(2.722)	(2.185)
Unit of observation	Household	Household	Household	Plot
Year fixed effect?	No	Yes	Yes	Yes
Village fixed effect?	No	No	Yes	No
Household fixed effect?	No	No	No	Yes
# obs	3,152	3,152	3,152	5,512
Adjusted R2	0.169	0.206	0.296	0.240

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.9: Demand for phosphorus at the intensive margin (all plots) (cont'd)

	kg P/ha					
	(5)	(6)	(7)	(8)	(9)	(10)
Land rental rates (KSH/ha/season)	0.657***	0.467***	0.143**	0.105**	-0.042	-0.009
	(0.097)	(0.087)	(0.059)	(0.052)	(0.057)	(0.052)
Ag. daily wage (KSH/day)	0.279*	0.273**	0.220*	-0.241***	-0.138	-0.183
	(0.145)	(0.129)	(0.131)	(0.086)	(0.121)	(0.132)
Phosphorus price (KSH/kg P)	-1.041***	-1.469***	-0.808***	-0.334	-0.087	0.104
	(0.130)	(0.274)	(0.238)	(0.223)	(0.203)	(0.120)
Hybrid maize seed (KSH/kg)	-0.320***	-1.652***	-0.237	-0.418	0.458**	-0.133**
	(0.105)	(0.298)	(0.257)	(0.314)	(0.236)	(0.067)
Maize prices (KSH/kg)	0.475**	0.711**	0.413*	0.357**	0.265	0.089
	(0.237)	(0.292)	(0.211)	(0.167)	(0.193)	(0.157)
Plot area (ha)				-0.017		1.026
				(0.029)		(0.035)
Year=2004		-0.422***	-0.176	-0.306**	-0.191**	
		(0.147)	(0.117)	(0.119)	(0.100)	
Year=2007		-0.982***	-0.152	-0.382*	0.111	
		(0.202)	(0.190)	(0.211)	(0.155)	
Year=2010		-1.504***	-0.238	-0.508	0.270	
		(0.247)	(0.260)	(0.314)	(0.238)	
Constant	1.764	13.045***	3.834	5.254*	1.531	4.053***
	(1.236)	(2.539)	(2.408)	(2.695)	(2.034)	(0.861)
Unit of observation	Household	Household	Household	Plot	Plot	Plot
Year fixed effect?	No	Yes	Yes	Yes	Yes	No
Village fixed effect?	No	No	Yes	Yes	No	No
Household fixed effect?	No	No	No	No	Yes	Yes
# obs	3,152	3,152	3,152	5,512	5,512	5,512
Adjusted R2	0.217	0.238	0.351	0.152	0.264	0.531

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.10: Demand for phosphorus on maize fields at the intensive margin (maize fields only)

	kg P			
	(1)	(2)	(3)	(4)
Land rental rates (KSH/ha/season)	0.338***	0.271***	0.080	-0.050
	(0.085)	(0.091)	(0.064)	(0.064)
Ag. daily wage (KSH/day)	-0.262*	-0.198	-0.265**	-0.090
	(0.148)	(0.156)	(0.123)	(0.153)
Phosphorus price (KSH/kg P)	-0.209	-0.053	-0.066	-0.022
	(0.169)	(0.279)	(0.154)	(0.321)
Hybrid maize seed (KSH/kg)	-0.289***	-2.001***	-0.756*	0.824***
	(0.104)	(0.529)	(0.417)	(0.365)
Maize prices (KSH/kg)	-1.394***	-1.645***	0.565**	0.557**
	(0.261)	(0.282)	(0.225)	(0.289)
Plot area (ha)				
Year=2004		0.389***	-0.125	-0.391***
		(0.144)	(0.081)	(0.145)
Year=2007		-0.705***	-0.380*	0.136
		(0.229)	(0.196)	(0.245)
Year=2010		-1.052***	-0.724**	0.410
		(0.400)	(0.350)	(0.362)
Constant	7.575***	17.175***	5.191**	-2.487
	(1.262)	(3.435)	(2.535)	(2.973)
Unit of observation	Household	Household	Household	Plot
Year fixed effect?	No	Yes	Yes	Yes
Village fixed effect?	No	No	Yes	No
Household fixed effect?	No	No	No	Yes
# obs	2,480	2,480	2,480	3,013
Adjusted R2	0.112	0.173	0.369	0.599

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Table 2.10: Demand for phosphorus on maize fields at the intensive margin (maize fields only) (cont'd)

	kg P/ha of maize					
	(5)	(6)	(7)	(8)	(9)	(10)
Land rental rates (KSH/ha/season)	0.411***	0.323***	0.040	0.016	-0.073	-0.024
	(0.075)	(0.067)	(0.045)	(0.051)	(0.056)	(0.053)
Ag. daily wage (KSH/day)	-0.259***	-0.267***	-0.269***	-0.233**	-0.088	-0.163
	(0.089)	(0.096)	(0.100)	(0.109)	(0.135)	(0.144)
Phosphorus price (KSH/kg P)	-0.198**	-0.463**	-0.080	-0.077	0.037	0.140
	(0.097)	(0.188)	(0.162)	(0.183)	(0.258)	(0.134)
Hybrid maize seed (KSH/kg)	-0.295***	-1.250***	-0.151	-0.239	0.764***	-0.203***
	(0.069)	(0.230)	(0.314)	(0.349)	(0.296)	(0.069)
Maize prices (KSH/kg)	-0.061	-0.136	0.556***	0.595***	0.489***	0.330**
	(0.155)	(0.164)	(0.179)	(0.180)	(0.216)	(0.171)
Plot area (ha)				-0.053*		-0.149***
				(0.030)		(0.044)
Year=2004		-0.118	-0.172*	-0.192*	-0.112	
		(0.103)	(0.090)	(0.102)	(0.130)	
Year=2007		-0.722***	-0.154	-0.175	0.365**	
		(0.150)	(0.180)	(0.195)	(0.205)	
Year=2010		-0.922***	-0.174	-0.201	0.655***	
		(0.218)	(0.293)	(0.321)	(0.292)	
Constant	3.390***	11.494***	2.444	2.699	-1.568	3.427***
	(0.729)	(1.912)	(2.249)	(2.451)	(2.497)	(0.891)
Unit of observation	Household	Household	Household	Plot	Plot	Plot
Year fixed effect?	No	Yes	Yes	Yes	Yes	No
Village fixed effect?	No	No	Yes	Yes	No	No
Household fixed effect?	No	No	No	No	Yes	Yes
# obs	2,480	2,480	2,480	3,013	3,013	3,013
Adjusted R2	0.097	0.128	0.230	0.233	0.469	0.471

Notes: Robust standard errors clustered at the village level and in parentheses below. All prices are in 2010 KSH. Maize prices are for the previous season (and inflation-adjusted appropriately). Nitrogen and phosphorus prices are from taking village-level weighted averages of the fraction of N or P coming from each fertilizer type multiplied by the KSH/kg N from that fertilizer type.

Finally, one concern with identification of the elasticities was that there may be simultaneity bias between fertilizer demand and crop choice, and between fertilizer demand and cultivated. While the results in section 2.5.1 show that demand for cultivated area does not change systematically with input prices, demand for area planted to maize was found to counterintuitively decrease with land rental rates and increase with fertilizer prices, i.e., $\beta_1 < 0$ and $\beta_3 > 0$. The results for demand for fertilizer at the intensive margin when restricting the sample to look only at maize plots is consistent with there being simultaneity bias arising from crop choice, though the sign of the bias is not consistent with the results in section 2.5.1.

If households increased the area of land planted to maize with land rental rates and decreased that area with fertilizer prices, or $\beta_1 > 0$ and $\beta_3 < 0$—which is, intuitively, what we would expect—then $\gamma_1$and γ_3, which should also have the same signs, would be biased away from zero, unless demand for area planted to maize were also controlled for. That is, $\gamma_1^{all\ crops} > \gamma_1^{maize}$ and $\gamma_3^{all\ crops} < \gamma_3^{maize}$,[46] which is what we see in tables 2.7 and 2.8, and in tables 2.9 and 2.10, and which is also consistent with intuition. This is further evidence of potential bias in the results without district fixed effects for demand for area planted to maize discussed in 2.5.1.

To summarize, once controlling for local growing and market conditions with a district fixed effect, the magnitudes of elasticities of conditional fertilizer demand with respect to input prices drop dramatically from when just year effects are included. Once controlling further for household-level average land quality and household characteristics, they drop further. Taken together, these results show that households change their fertilizer use in response to changing input prices, but that the degree to which they do so is not especially large.

[46] $\gamma_1^{all\ crops} = \frac{\partial z}{\partial r} + \frac{\partial z}{\partial A^{maize}} \times \frac{\partial A^{maize}}{\partial r} > \gamma_1^{maize} = \frac{\partial A^{maize}}{\partial r}$, since $\frac{\partial z}{\partial r} > 0$, and we would expect $\frac{\partial z}{\partial A^{maize}} > 0$ and $\frac{\partial A^{maize}}{\partial r} > 0$. Similar logic holds for fertilizer demand, except that $\frac{\partial z}{\partial p^z} < 0$ and we would expect $\frac{\partial A^{maize}}{\partial p^z} < 0$.

2.5.4 Farm labor demand

Changes in household size and composition over the 13-years of the survey are shown in table 2.11. In 1997, households had an average of 6.65 members and 6.07 adult equivalents; by 2010, these had dropped to 5.51 and 4.75, respectively. These changes are relatively small, but the decrease is consistent across survey years. The drop in adult equivalents is also slightly larger than that in household size (a change of 1.32 versus 1.14). While this table is merely descriptive and should thus be interpreted with caution, the trends shown here provide an indication as to household labor supply over the course of the survey. Given the heavy reliance on family labor supply for farm labor, as discussed previously, this in turn gives an indication as to how farm labor demand may be changing.

Adult equivalents are defined in table 2.12, and their decline over time can be attributed to either household members aging past 18 years old, births, or the departure of a household member for any reason. The decrease in household size between 1997 and 2010, however, rules out births as the primary driver of the drop in adult equivalents, unless 1-2 adult members also left the household (for any reason).

Table 2.11: Mean household size and adult equivalents 1997-2010

	1997	2004	2007	2010
Household size	6.65	6.09	5.86	5.51
	(2.60)	(2.95)	(3.03)	(3.00)
Adult equivalents	6.07	5.21	5.02	4.75
	(2.30)	(2.51)	(2.57)	(2.59)
Number of households	1,208	1,208	1,208	1,208

Notes: Standard deviations in parentheses below. All years different from other years at p=0.01 except for 2004 and 2007, where household size is different at p=0.1 and adult equivalents are different at p=0.05. Household size is defined as the number of members resident in the household in the corresponding year.

It is possible that the decrease is instead mostly due to the aging of household members over the course of the survey. As shown in table 2.12, changes in adult equivalents from one age group the next are fairly small, even over 13 years: the biggest potential decrease in this timeline would be from a male aging out of the 30-60 year category into the 60+ category, followed by an 18 year old male turning 31 by the 2010 survey. Even under the implausible assumption of households composed exclusively of men of these ages, the corresponding decreases in adult equivalence, 0.16 and 0.14, respectively, coupled with the average household size of roughly 6 members, are too small to explain the average drop of 1.32 adult equivalents between 1997 and 2010.

On the other hand, the departure of a household member, either due to death or migration, is consistent with the overall trends observed in table 2.11. It is possible that, given that these same households were tracked over 13 years, some of the decrease in household size and adult equivalents is due to the decease of elderly members. Alternatively, it could that household members who are old enough are migrating away—for school, work, or marriage. Migration for any of these reasons could ultimately be due to rising land pressures and limited participation in local labor markets, which would be consistent with Muyanga & Jayne's (2014) findings that off-farm income increases only marginally with population density.

Table 2.12: Adult equivalence

Gender	Age	AE
Both	<1 year	0.33
Both	1-2 years	0.46
Both	2-3 years	0.54
Both	3-5 years	0.62
Male	5-7 years	0.74
Male	7-10 years	0.84
Male	10-12 years	0.88
Male	12-14 years	0.96
Male	14-16 years	1.06
Male	16-18 years	1.14
Male	18-30 years	1.04
Male	30-60 years	1.00
Male	>60 years	0.84
Female	5-7 years	0.70
Female	7-10 years	0.72
Female	10-12 years	0.78
Female	12-14 years	0.84
Female	14-16 years	0.86
Female	16-18 years	0.86
Female	18-30 years	0.80
Female	30-60 years	0.82
Female	>60 years	0.74

Source: Tegemeo Survey Documentation 2010

2.5.5 Discussion

Putting this together, several overarching patterns stand out. Across all specifications, households do not adjust production at the extensive margin, through area cultivated, with changes in either land or labor prices. It is not clear that they do so with changes in fertilizer prices either. There is some substitution away from planting maize as land prices rise across districts, but this does not hold once controlling for district-level growing and markets conditions, land quality, and other factors. Overall, it appears that maize comprises a lower share of cultivated land in areas with high land prices, which could be explained by maize providing less revenue—and therefore being less profitable—than cash crops. Fertilizer use on maize fields specifically is less elastic with respect to land rental rates than that applied to all fields, possibly reflecting already-high application rates on maize.

Households do appear to increase fertilizer use in response to rising land prices, though the degree to which they do so is not especially large, once controlling for district-level growing and market conditions and land quality. At the plot level and with the inclusion of a household fixed effect, they drop further. Across all specifications, households do not appear to adjust input use in response to the market wage. These results are partially consistent with Boserup's theory—that households will increase fertilizer use in response to rising land prices—but also suggest that households face additional constraints in fertilizer use that limit the degree to which they adapt to changing factor prices. Moreover, these findings are evidence against the null hypothesis that households adjust input use based solely on relative factor prices.

Much of Kenya's success in increasing fertilizer use over the past two decades has been attributed to the liberalization of fertilizer markets and the sharp drop in costs associated with purchasing fertilizer. Together, these results indicate that strategies meant to improve how households cope with rising land pressures would do well to first examine the functioning of other factor markets. Which markets and which types of policies are likely to be effective are beyond the scope of this paper, but there are several promising suggestions elsewhere in the literature. Jin & Jayne (2013) emphasize the need for policies to reduce costs associated with participating in land rental markets in Kenya, a recommendation that is supported by my findings. Dillon et al. (2017) provide evidence of imperfect labor markets elsewhere in East Africa, while Bryan et al. (2014) and de Brauw et al. (2013) show that there are potentially large gains to reducing the costs associated with seasonal migration. Given the low response of household off-farm income to rising population density and land prices in Kenya, as found by

Muyanga & Jayne (2014), it seems likely that there are high costs to migration and limited off-farm income earning opportunities in rural Kenya. Lowering costs to participate in land and labor markets, and strengthening rural non-farm sectors are all promising candidates for policy meant to increase smallholders' adaptability to rising land pressures.

2.6 Conclusion

Given rising land pressures throughout rural sub-Saharan Africa, it is increasingly urgent to understand how (and whether) smallholders adapt to changing factor prices. This study used a 13-year panel of 1,208 smallholders in Kenya to show that, while fertilizer use does increase with land prices, this is primarily due to movement across districts and aggregate trends over time. Once controlling for district-level conditions that may affect the profitability of fertilizer use, a doubling in land rental rates would only increase households' propensity to apply nitrogen through inorganic fertilizer by 4.5% and conditional dosage rates by 30.3% of the 2010 standard deviation. Within households, the effect of land rental rates on conditional fertilizer use is not statistically different from zero, and the effect on the propensity to use fertilizer on a given plot is small—with an elasticity of only 0.029. Fertilizer demand is similarly unresponsive to changes in market wages. Consistent with these findings, households do not decrease production at the extensive margin, through the quantity of land they cultivate, as a result of increasing land prices.

Overall, the low short-run elasticity results demonstrate that households are not responding flexibly to changes in land or labor prices. Instead, they appear to be increasing fertilizer use with decreases in fertilizer prices—with a household-level elasticity of -0.408, or 49.7% of the 2010 standard deviation for conditional nitrogen dosage rates—and over time. Relatedly, community and household characteristics seem to matter, as demonstrated by the considerable decrease in elasticity magnitudes when controlling for these characteristics through fixed effects. For example, it may be that households in villages which are better connected to other markets and urban centers may face lower transaction costs and participate more actively in factor markets. Similarly, those located in higher potential agro-ecological zones may find it worthwhile to continue to invest in agricultural production, while those in lower potential zones may be more inclined to leave agriculture altogether if the cost of cultivation becomes too high. Households with higher levels of assets or education may find it less costly to seek employment opportunities elsewhere. Identifying these potential sources of heterogeneity is a key next step for future research.

A related and important next step is determining what the constraints to input use are and the degree to which they ultimately limit households' abilities to adapt. Although this paper showed suggestive evidence that market frictions, possibly including high transport costs, do inhibit the degree to which households adjust input use, studies such as Karlan et al. (2014), Duflo et al. (2011), and Bryan et al. (2014) are needed to pinpoint more precisely households' binding constraints and, ultimately, what happens when they are relaxed. Such work is crucial to guiding policies to improve smallholders' adaptability to increasing land pressures and changing farming systems.

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3 SIFTING THROUGH THE WEEDS: UNDERSTANDING HETEROGENEITY IN FERTILIZER AND LABOR RESPONSE IN CENTRAL MALAWI

3.1 Introduction

Two consecutive years of poor growing conditions in Malawi has resulted in millions of smallholders unable to support themselves until the next harvest (UN News Centre, 2015).[47] With increasing variability in yields due to climate change and degraded soils, programs to improve agricultural productivity have become ever more critical. In recognition of this challenge, the Malawian government has for the past decade allocated over half of its agricultural spending, amounting to nearly $200 million annually, on subsidizing fertilizer and seed for smallholder farmers (Jayne & Rashid 2013). While this program has led to increased fertilizer application rates (Ricker-Gilbert et al. 2011), yields have risen only moderately since the subsidy program began in 2004/05 (Dorward & Chirwa 2011), and Malawi has yet to see the dramatic improvement in yields that Asia experienced during its Green Revolution. Nor is it clear whether most Malawian farmers would continue to use fertilizer if it were not heavily subsidized.

This paper identifies the factors limiting maize production, the profitability of fertilizer use, and, relatedly, why some farmers report high nitrogen response rates while for others the effect of inorganic fertilizer on yields is too little to justify its cost (Wiyo & Fenen 1999; Ricker-Gilbert et al. 2011; Kamanga et al. 2014). Despite an extensive literature on the FISP program, there is no clear consensus on estimates of fertilizer response rates, which range from negative returns to 18.0 kilograms of maize per kilogram of nitrogen applied (Chirwa & Dorward 2013,

[47] This chapter is co-authored with Thomas S. Jayne and Sieglinde S. Snapp.

Wiyo & Feyen 1999). This broad array of fertilizer response estimates has been attributed to differences in soil properties, the intensity and timing of fertilizer application, and weeding (Snapp et al. 2014; Tittonell et al. 2008), but empirical analysis of these interactions remains limited.

We begin to fill these gaps in understanding of heterogeneity in maize response to inputs through a two-year plot-level panel survey of farmer-managed maize plots in Central Malawi. Our detailed dataset, which tracks farmers' self-identified most and least fertile maize plots in two consecutive growing seasons, allows us to identify characteristics of plots and farmers who are able to use fertilizer profitably and to better understand the range of fertilizer response rates found in two districts in Central Malawi. We identify both village-level and household-level sources of this heterogeneity. We also model how maize response to fertilizer changes with weeding rates, dependent on soil, crop, and climate characteristics.

In this study, we focus on the role of weeding labor and soil characteristics for several reasons. It is well-established in the agronomic and soil science literature that weeds compete with maize and other crops over soil nutrients (Zoschke & Quadranti 2002), and an excess of weeds has been found to be the third main limiting factor in maize yields after water and nitrogen (Gholamhoseini et al. 2013), reducing maize yields by up to 70% (Mohammadi 2007). The interactions between water, nitrogen, and weeds are complex and vary by climate conditions, soil types and fertility, and crop and weed species and density.

The link between weeding labor and maize response to nitrogen has been explored in on-farm trial plots in central Malawi. Two weedings, particularly in the presence of nitrogen applications, improves yields significantly (Kamanga et al. 2014). However, to our knowledge there are no non-experimental studies of weeding among smallholders, nor are there experimental ones using more precise measures of weeding labor. What has been shown is that yields and input response rates from trial plots often represent what is achievable under ideal circumstances, rather than what is realistic on farmer-managed plots, where real-world time and financial constraints apply. Moreover, few economic studies of input use explicitly account for weeding labor and its interaction with fertilizer response rates, potentially neglecting a key component of fertilizer use efficiency in Africa. This study contributes to the literature by providing a greater understanding of the importance of weeding in influencing maize response to fertilizer application on farmer-managed plots that reflect the myriad resource constraints faced by smallholder farmers.

The role of soil organic matter (SOM) in influencing crop response to inorganic fertilizer is also of increasing interest to researchers. Numerous studies, such as Marenya and Barrett (2009) and Blanco-Canqui et al. (2013) show that maize response to nitrogen is contingent on the level of SOM present. That is, in soils with little organic matter, fertilizer application will not result in the same increase in yields as compared to soils with higher levels of SOM, and in severely degraded soils, fertilizer application may even decrease yields (Zingore et al. 2007; Marenya & Barrett 2009). Soil organic carbon (SOC) is the structural background of SOM; as such, the two are highly correlated. SOC has been shown to affect agronomic productivity through nutrient availability and water-holding capacity (Lal 2006, Blanco-Canqui et al. 2013). Increases in SOC decrease the variability of yields in response to weather shocks, thereby lowering risk while increasing yields (Graff-Zivin and Lipper 2008). Historical data shows moderate to low levels of SOC in Malawi’s soils, a problem likely exacerbated in recent years by continuous cropping and reduced fallows (Snapp 1998; Woomer et al. 1994; Pieri 1995; Snapp 2002).

We build on these studies by estimating how maize response to fertilizer and weeding labor changes with soil fertility, using two different measures. Our first measure is the level of soil organic carbon. Following previous studies (e.g., Marenya & Barrett 2009), we use total organic carbon (hereafter referred to as total C) as our measure of interest, as it is slow to change and is thus a measure of long-term carbon levels (Brady & Weil 2007). We also include soil texture. Soils high in clay and silt tend to be higher in organic matter, and differences in organic matter within a local area can often be attributed to differences in soil texture (Brady & Weil 2007). Moreover, the clay content of soil plays a key role in stabilizing nitrogen (ibid.). Although soil acidity has been cited elsewhere as a key determinant of maize yields, with plant growth and nutrient uptake being severely limited highly acidic soils (below a pH of 4.4) (Zambia Agricultural Research Institute, 2002), the evidence on this being the case in Malawi is inconclusive (Kabambe et al. 2012; Snapp et al 2014), and pH is excluded for reasons discussed in greater detail below.

We also use a coarser measure of soil fertility by splitting the sample into the most and least fertile plots according to their levels of total organic carbon (total C) to better characterize the range in maize response to inputs according to plot fertility. Our study is unique in that its panel design allows us to control for unobserved plot-level heterogeneity while also allowing us to characterize the upper and lower bounds of input response within our sample. We use these input response estimates and village-level price data to understand the range of profitability of input use by way of value cost ratios. While the majority of the literature focuses on the factors limiting yields, this study focuses on those which affect profitability of inputs. Inputs are costly, and it is not clear that increasing fertilizer application rates is profitable for any given smallholder on any given plot, given the wide range in response rates that they currently obtain.

Despite the prevailing view that Malawi is a labor-abundant, land-scarce country, there is limited evidence that the returns of additional farm labor are high enough compared to alternative uses.

Finally, we compare our objective soil fertility classification to farmers' own identification of their most and least fertile maize plots. This latter, subjective grouping allows us to account for plot characteristics not otherwise captured, such as proximity to water sources, as well as potential differences in farmer effort, such as if the farmer-identified high fertility plot is prioritized in receiving inputs. This section builds on recent work showing that farmers' subjective soil fertility ratings often do not correspond with objective measures (Berazneva et al. 2018). It also contributes to a growing literature on mismeasurement in agricultural statistics, including work on land measurement bias (Dillon et al. 2016), production statistics (Deininger et al. 2012), recall bias (Beegle et al. 2012a, 2012b), and labor statistics (Bardasi et al. 2011). By comparing yield response to input use when plot fertility is identified by farmers to that when using an objective measure of fertility, we begin a preliminary assessment of the degree to which bias from farmers' perceptions of relative plot fertility may affect estimates of input productivity.

We find that maize response to fertilizer and weeding labor varies significantly between the most and least fertile plots in our sample and that these differences are not solely attributable to farmer skill, as these differences persist even with the inclusion of plot fixed effects. Our calculated average and marginal value cost ratios (AVCR and MVCR, respectively) indicate that fertilizer application at observed rates is profitable on a higher percentage of the least fertile plots than on the most fertile, even though fertilizer was applied at higher rates on the low fertility plots. Conversely, despite receiving comparable rates of weeding labor, nearly 70% of the most fertile plots would benefit from increased weeding labor intensity, while under half of the least fertile would. These findings imply that policies aimed at increasing input application rates and productivity should be tailored to address smallholder farmers' highly heterogeneous plot-specific conditions.

The rest of the paper is organized as follows: section 3.2 outlines a theoretical framework for a profit-maximizing smallholder farmer, followed by a description of the data used in this study. We then present our empirical strategy and results from estimation of input physical products. Section 3.6 describes the profitability analysis scenarios and results, while section 3.7 discusses differences according to objective versus subjective classifications of most and least fertile. We conclude by summarizing the main findings and considering their implications for government actions to promote the profitable use of fertilizer by Malawian farmers.

3.2 Theoretical motivation

Due to limitations imposed by our sample size and our desire to focus on the technical relationship between fertilizer, weeding labor, and soil characteristics, we make several simplifying assumptions in our setup. First, we assume that our sample of agricultural households are profit-maximizing and face a recursive optimization problem, where they first maximize expected profits from production, which then inform consumption choices. Although the preceding chapters assumed that households' farm production decisions are non-separable from consumption decisions, our interest here lies in characterizing the interactions between inputs and soil characteristics, as well as in the range in input profitability within and across households—technical relationships which are not changed by the simplifying assumption of profit maximization. The key implications of a non-separable problem, such as differences between hired and family labor, and the impact of household characteristics on input demand functions, are difficult to test, given our sample size, and are not our primary focus.

One concern in treating the household's problem as separable is if input and output markets are incomplete, so that input demand and maize supply do not depend solely on prices. However, given fertilizer use rates among the farmer in our sample and anecdotal evidence as to the widespread availability of fertilizer in the study area, it is plausible to assume that fertilizer markets are relatively complete. Maize markets are similarly competitive, so that farmers can buy and sell maize as desired, lending credence to the assumption that farmers' valuation of their own maize is equivalent to its market prices. Labor markets are most likely to be incomplete, as supported by recent evidence (Dillon et al. 2017). With only 10% of our sample hiring in labor, however, we lack the data to test for substitution effects of labor provided by different groups, and pooling labor provided by different types of laborers allows us to better examine the overall interactions between weeding labor, fertilizer application, and maize yield. Under these assumptions, then, the household allocates labor and other inputs to maximize expected profits from maize production, or:

$$\max E(\pi) = E(p^y)y - p^N N - wL - p^z z \tag{1}$$

$$y = f(N, L, z, s;\ \theta) \tag{2}$$

That is, a household's profit π is given by its revenue by selling maize, y, multiplied by the market price p^y, less the quantity of nitrogen N applied through inorganic fertilizer multiplied by nitrogen's market price p^N, labor inputs L multiplied by the market wage w, and material inputs (excluding nitrogen applied through inorganic fertilizer) z multiplied by their prices p^z. Maize production depends on these inputs, as well as plot and soil characteristics s and exogenous shocks θ.

We are interested in how π changes with s, z, and L, and N, and how π*'s* response to both nitrogen and weeding labor is impacted by s, soil characteristics, and each other. Substituting (2) in (1), we see that the direct effect of nitrogen application on profits is through its impact on yields and its costs. The total effect of nitrogen application on yields is found by totally differentiating (2) with respect to nitrogen, or:

$$\frac{dy}{dN} = \frac{\partial y}{\partial N} + \frac{\partial y}{\partial L}\frac{dL}{dN} + \frac{\partial y}{\partial z}\frac{dz}{dN} + \frac{\partial y}{\partial s}\frac{ds}{dN} + \frac{\partial y}{\partial \theta}\frac{d\theta}{dN} \tag{3}$$

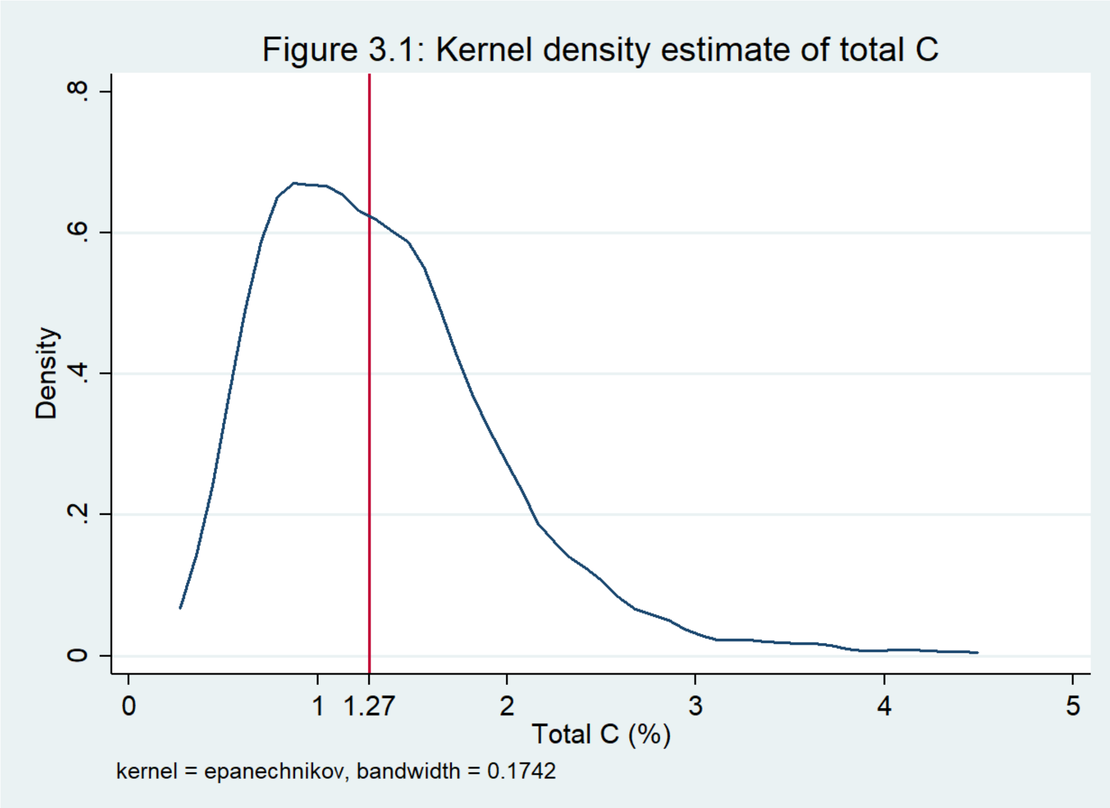
Where the final term, $\frac{\partial y}{\partial \theta}\frac{d\theta}{dN}$, drops out since θ is an exogenous shock and so $\frac{d\theta}{dN} = 0$. The overall change in yields with respect to nitrogen application then depends on the direct effect of nitrogen application, as well as interactive effects through other inputs, L and z, and soil and plot characteristics s. Similarly, the overall change in yields with respect to labor inputs depends on the direct effect of labor plus indirect effects through its interactions with other inputs and soil and plot characteristics.

3.3 Data

The data for this study come from a panel dataset of approximately 300 households in two regions of Central Malawi surveyed as part of the Africa RISING project. In Dedza district, a total of approximately 150 households from three different extension planting areas (EPAs) were chosen, and a similar number were chosen from two different EPAs in Ntcheu district. The EPAs were selected to represent the range of possible growing conditions in Malawi, with one being considered a high potential zone, two medium potential, and two low potential zones. Farmers were divided into 3 groups: those participating in the Africa RISING program (intervention households), those not part of the Africa RISING program but living in the same villages in which the program operates (local control), and those in villages with no Africa RISING presence (distant control). Of the five EPAs, three contain households in all three sample groups, a fourth contains intervention and local control households, and the fifth contains distant controls for that fourth EPA. We discuss potential implications of program participation below.

In September 2014, farmers from the selected households were asked to identify their most and least fertile maize plots. Farmers were additionally asked about soil amendments, yields, and labor inputs for the previous growing season. Soil samples were obtained from the plots identified by the farmers and analyzed for carbon and nitrogen content, pH, and texture. Given the timing of data collection, both pH and soil nitrogen content are excluded from this analysis, as they are likely to have been affected by inputs applied in the 2013-2014 growing season. The other soil characteristics of interest—texture and total organic carbon—are unlikely to have been significantly affected by the previous season's input use (Brady & Weil 2007).[48] The same plots were revisited both in March 2015 and May 2015 to obtain data on input and planting decisions, as well as to calculate yields through taking yield cuts on a 2 meter by 2 meter area. Given our interest in characterizing the range in profitability of input use, rather than differences in farmers' input decisions on their subjective rankings of most and least fertile plots, we recharacterize plots as most or least fertile on the basis of their total carbon for our main analysis. Without a clear cut point in the distribution of total C on all plots, we split the sample at the median value of total C but discuss the implications of doing so in greater detail below. The distribution of total C is shown in figure 3.1 and the geographic distribution of high versus low fertility plots according to local growing conditions is shown in figures 3A.1 and 3A.2 in the appendix.

[48] This may not hold for other measures of soil organic carbon, such as active carbon (POXC). Total organic carbon is slow to change, however, and it is thus unlikely that the previous season's inputs had a noticeable effect on its level (Brady & Weil 2007).



Notes: Median total C value of 1.27% denotes cutoff for high and low fertility plots.

Plot-level descriptive statistics of the key variables included in the maize response equation, pooled across years, are shown in table 3.1. In computing the quantity of inputs applied to plots, we make several simplifying assumptions. There are a number of types of inorganic fertilizer available in Malawi, each with different compositions of key nutrients. It is the impact on maize yields of nitrogen applied through inorganic fertilizer, rather than the impact of inorganic fertilizer generally speaking, that is of greatest interest, as nitrogen is critical for both increasing yields and improving stability of yields (Vanlauwe et al. 2013) and has found to be a limiting factor in Malawi's maize productivity (Snapp 1998; Snapp et al. 2014). The two primary types of inorganic fertilizer used on maize in Malawi are NPK (23:21:0+4S) and urea (46:0:0), with CAN (26:0:0) also widely used. We use the nitrogen content of each fertilizer type—23% for NPK, 46% for urea, and 26% for CAN—to aggregate across fertilizer types and calculate the total quantity of nitrogen applied to each plot. We do not account for potential differences in fertilizer quality and application rates of phosphorus, but discuss these potential biases in qualifying our results.

Using a subsample of the data for which we have seeding rates, we find that, conditional on these rates, planting labor does not significantly impact yields, and the same holds for fertilizing labor, conditional on fertilizer application rates. Finally, while maize response to fertilizer could plausibly be affected by land preparation activities, we find no statistically significant effect. For these reasons, and due to sample size restrictions, we pool these three types of labor and include them as a control in the production function without disaggregating further. As have others, we do not include harvest labor as an input in production, as it occurs when production is complete (Dillon & Barrett 2017). The time reported for labor activities is adjusted by the hours per day that farmers reported spending on each plot to arrive at an adjusted person-day spent on each activity. Despite this adjustment, the overall days of labor reported per hectare are high, an issue we address further in interpreting the results.

Given the potential for overly high input use rates and yields when standardizing by a per hectare measure, we drop plots below 0.05 hectares in area. We also drop plots on which input application rates or yields exceeded the 99th percentile (95th in the case of labor) in the sample, so that only plots on which nitrogen was applied below 400 kg/hectare, yields were below 6400 kg/hectare, and on which weeding labor and other labor activities (land preparation, planting, and fertilizing) were below 600 days/hectare and 865 days/hectare, respectively. Doing so leaves us with 310 unique plots on which maize was planted in at least one survey year; with the two years combined, we have 438 observations. Interestingly, both 2014 yields and nitrogen application rates in both years are significantly higher on the low fertility plots than the high, with 2014 yields of 1597 kg/ha on the high fertility plots and 1969 kg/ha on the low, and, across both years, nitrogen application rates of 59 kg N/ha on the high plots and 74 kg N/ha on the low. Average yields across two years are slightly higher on the low fertility plots than the high, though the difference is not statistically significant. This holds when looking at within-household, within-year differences, as described in greater detail in section 3.7. While the lack of yield difference may call into question the validity of total C as an objective measure of soil fertility in our study, we proceed as planned for three key reasons. First, it is widely used elsewhere as a measure of soil fertility. Second, it is a truly objective measure that is (relative to yield and input profitability) uninfluenced by farmer effort and other observable factors. Third, our interest in characterizing the range in productivity—rather than in making claims as to the best measure of soil fertility.

Maize price data comes from the Malawi Agricultural Information System (AMIS), which collects monthly price data from markets across Malawi. Each cluster of villages was matched to the nearest AMIS market, which is either a road town or the district capital, depending on the market. While wholesale prices found at large markets already take into account the transactions costs associated with transporting maize to the market and are unlikely to directly match those offered to farmers at the farm gate, it is plausible that farmers within the same geographical location will experience similar transportation costs or will be offered similar prices by traders purchasing in the village. Detailed price information is in tables 3A.5 and 3A.6 of the appendix.

Table 3.1: Summary statistics of key variables used in analysis by plot (years pooled)

	High fertility plots (n=217)				Low fertility plots (n=221)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Plot-level inputs and output								
Maize yield (kg/ha)	1472.5	1042.3	63.7	5867.4	1650.7	1311.4	109.3	5945.6
kg N/ha	59.1	61.1	0	289.7	74.1	77.9	0	393.8
Total weeding days/ha	130.0	108.2	5.4	491.3	132.6	110.4	0	498.6
Other labor activities (days/ha)	174.8	122.0	5.4	565.1	174.9	118.2	13.6	578.8
Hybrid maize seed (1=yes)	0.35	0.48	0	1	0.45	0.50	0	1
Soil characteristics								
Total C	1.82	0.53	1.27	4.32	0.89	0.21	0.44	1.27
% clay in soil	33.0	19.2	7.6	87.6	26.7	16.4	5.6	87.6
% sand in soil	53.3	23.0	2.6	86.6	62.7	20.7	2.6	88.4
Plot characteristics								
Plot area (ha)	0.27	0.20	0.05	0.99	0.26	0.18	0.05	0.97
Moderate or steep slope	0.12	0.32	0	1	0.10	0.29	0	1
Plot flooded in 2015 (1=yes)	0.11	0.31	0	1	0.11	0.31	0	1

3.4 Empirical strategy

To understand the overall (expected) effects of nitrogen application and weeding labor, we first estimate the different components that contribute to overall expected change in yields with respect to fertilizer and weeding labor—the righthand sides of equation (3) and its counterpart for labor. With a plot-level panel of farmers' most and least fertile maize plots, we are able to test a number of specifications to determine the stability of our results.

There is a key caveat to our approach. While we recognize that inputs are not randomly allocated and are therefore endogenous to production, we are interested in the technical relationship between inputs and outputs, rather than the causal impact of an additional unit of inputs on maize yield, and our sample size limits our ability to account for endogeneity in choice variables. Our results are thus not meant to be interpreted causally but rather as an exposition of the range in maize response to fertilizer and weeding labor within and between households, as well as under varying soil characteristics and quantities of other inputs.

Our general specification follows that typically found in the literature and is a maize response function which includes quadratic terms for nitrogen application and weeding labor, as well as interactions between the variables of interest:

$$y_{eijt} = \beta_0 + \beta_1 N_{eijt} + \beta_2 N^2_{eijt} + \beta_3 L_{eijt} + \beta_4 L^2_{eijt} + \beta_5 z_{eijt} + \beta_6 s_{eijt} + \beta_7(s_{eijt} \times N_{eijt}) + \beta_8(s_{eijt} \times L_{eijt}) + \beta_9(N_{eijt} \times L_{eijt}) + EPA_e \times year_t + \varepsilon_{eijt} \quad (4)$$

Where maize yield *y* of household *i* in EPA *e* on plot *j* and year *t* depends on nitrogen application *N* and its squared term, labor and its squared term *L*, other inputs *z*, plot and soil characteristics *s* (which includes an indicator for whether it is the high or low fertility plot), interactions between plot and soil characteristics and nitrogen,[49] plot and soil characteristics and labor, and nitrogen and labor. We also include a location-year fixed effect to control for differences in growing conditions and in soil fertility—given an unequal geographic distribution of high and low fertility plots—across geographic locations and years. While yields are stochastic and unknown at the time of planting, we drop the expectation notation for simplicity.

We first estimate the technical relationship as given in equation (4) via pooled OLS (POLS).[50] We then exploit the plot-level panel structure of the data and estimate (4) using plot-level fixed effects (FE). Doing so has significant benefits. Despite the detailed plot-level soil data, there are likely to be plot characteristics that affect the profitability of input use but were not included in our data, including soil characteristics that were not measured, or proximity to the nearest water supply. Moreover, since plots are cultivated by the same manager in each of the two survey waves, the plot fixed effect controls for time-invariant farmer heterogeneity, including overall experience and knowledge of that particular plot, which would affect the profitability of input use and bias OLS estimates. Fixed effects estimation also differences out time-invariant sources of measurement bias, such as if certain households are more likely to overreport input use than others, which is a particular concern given the high levels of labor reported. With two consecutive years of data, it is plausible that most of these potential sources of variation are in fact time-invariant.

In a similar vein, the soil characteristics used in this study—total C, and texture—change slowly enough to be considered time-invariant over a two-year period and so drop out of the

[49] We exclude the interaction between nitrogen application and the square of total C because its inclusion resulted in multicollinearity, though in a larger sample this additional term may be important in modeling the relationship between total C and nitrogen.

[50] We also follow the approach of much of the literature on fertilizer profitability and maize production and estimate equation (4) in levels, though the overall pattern of results also holds when estimating in logs.

fixed effects estimation, though the interactions between total C and nitrogen application and weeding labor do not, because these latter two variables can vary substantially on a given plot from one year to the next. The plot and soil characteristics, as well as the indicator for whether the plot is categorized as high or low fertility, are included to control for observable factors which may influence maize response to inputs and resulting input allocation decisions.

While plot-level fixed effects controls for time-invariant unobserved heterogeneity at both the plot and household levels, it cannot correct for potential bias arising from the endogeneity of input use decisions. Similarly, if participation in the Africa RISING program leads to changes in farmer skill which differs between the two growing seasons, this unobserved time-variant heterogeneity will bias our results. It is difficult to test whether this is the case, given both the timing of data collection (with the first growing season occurring 6 months after the program began) and the differences in data collection between the two years (using recall data in the first year and yield cuts in the second). As shown in table 3A.4 of the appendix, treating the first growing season as the baseline, and assuming that all recall data is biased in the same direction, we find no "treatment effect" on maize response to weeding labor. We do find evidence of a treatment effect on maize response to nitrogen among intervention households but not among the local controls. We also find that distant control households had higher maize yields than either the local control or intervention households in the second wave of the survey. With a high degree of spatial variation in weather patterns, this difference in yields could be accounted for by more favorable weather in the distant control villages in the 2015 growing season, so it is difficult to draw any conclusions from that finding. Given our findings of a treatment effect among intervention households only, we estimate the maize response equation using fixed effects with a restricted sample which excludes intervention households as a robustness check.

As another robustness check, we use a control function (CF) approach to account for the endogeneity of weeding labor. We instrument for weeding labor, rather than other inputs, for a number of reasons. First, weeding labor is the sole input for which we have strong instruments. In the absence of strong instruments, OLS is preferred to instrumental variables approaches because the low correlation between weak instruments and the endogenous variable magnifies the bias (Wooldridge 2010).

Moreover, weeding labor is influenced by the level of weeds on a plot, which is generally correlated with the plot's fertility as well as other previously applied inputs, such as fertilizer. This is particularly problematic in estimating the interaction between nitrogen and weeding labor: the quantity of weeds on a plot increases with fertilizer application, but weeds compete with maize for nutrients in the soil. If the intensity of weeding labor remains constant through an increase in fertilizer application rates, the diversion of some nitrogen from maize to weeds would result in an underestimate of maize response to fertilizer, when the cause is in fact less nitrogen going to the crop due to insufficient weeding. Whether the plot was sufficiently weeded cannot be identified with this data, but instrumenting for weeding labor helps account for these identification issues.

With weeding wage data for only the 2014/15 growing season, we lack the data to use the full sample to implement the control function in both years and so use only data from that year for this robustness check. As suggested by our pooling of family and hired labor in equations (1)-(2), we use measures of labor endowment and local wages to instrument for weeding labor inputs. The control function is implemented by first regressing family weeding labor on the full set of covariates from the maize response equation and excludable instruments of labor endowment and local wages, and then include the residuals in estimation of equation (4).

Across all three estimations, our primary interest lies in the overall marginal effects of nitrogen application and weeding labor, the heterogeneity in marginal effects between plots, and the signs of their interactions with soil carbon and each other. We expect that returns to fertilizer and labor will be higher on plots with higher levels of total C. If farmers' identification of their most and least fertile plots corresponds to total C, we expect to find similar differences in response rates of maize to fertilizer and weeding across high and low fertility plots.

3.5 Results

We first present the overall estimated effects of nitrogen application and weeding and land preparation labor on maize yield. Marginal effects of these three inputs from all three estimations are reported in table 3.2, while key regression results are below in table 3.3, with the full set of results in table 3A.2 of the appendix. Marginal effects were computed using the margins command in Stata, which uses the delta method to calculate standard errors and p-values. In the OLS estimations, the high fertility plot fertilizer marginal effect, at 3.5 kg maize/kg N is significantly smaller than the marginal effect on low fertility plots, at 9.8 kg maize/kg N. This trend holds when controlling for unobserved time-invariant plot and farmer heterogeneity, with the fixed effects estimation. The magnitudes are smaller, however, with marginal effects of 2.6 kg maize/kg N and 6.5 kg maize/kg N on the high and low fertility plots, respectively. On the high fertility plot, the coefficient is very imprecisely estimated, while on the low fertility plot it is statistically different from zero at the 10% level. That said, these results further call into question whether total C adequately proxies for soil fertility.[51]

The control function point estimates are smaller still, at 1.6 kg N/kg maize on the high fertility plots and 3.9 on the low. As with the fixed effects results, the high fertility plot point estimates are not statistically different from zero, while the low fertility estimates are marginally significant. The CF results should be interpreted with caution, however, given the small sample size (218 observations). The difference in results between the OLS and fixed effects estimations suggests potential bias caused by plot- and farmer-level time-invariant heterogeneity, despite our inclusion of plot and soil characteristics.

As mentioned previously, our aggregation of fertilizer application by nitrogen content necessarily masks heterogeneity in nutrient composition and application rates and timing. Farmers applied NPK (applied at planting time) at slightly higher rates than urea (applied as a top dressing typically 4-6 weeks after planting), with application rates of 98.1 kg NPK/ha and 84.2 kg urea/ha, respectively, and differences in nitrogen content also mean that different quantities of nitrogen were applied at different times. While fertilizer application timing is critical to maximal nutrient usage (Jones & Jacobsen 2003), it was not found to be significant in this analysis. Similarly, while phosphorus content varies by fertilizer type, and Malawi's soils have been found to contain sufficient to low levels of phosphorus (Snapp 1998), our analysis shows that nitrogen is the limiting factor, with neither contemporaneous nor lagged phosphorus

[51] Given the breakdown of high and low fertility plots, using the objective classification, across EPAs, finding a higher marginal effect of nitrogen application on the low fertility plots than the high is especially surprising. As can be seen in figure 3A.1, high fertility plots are disproportionately located in Linthipe, a high potential growing zone, and Kandeu, a medium potential growing zone. Low fertility plots are disproportionately located in Golomoti and Mtakataka, both low potential zones. On the other, low fertility plots are disproportionately cultivated by distant control households, which applied fertilizer at significantly lower rates yet, for the most part, realized higher yields than did the intervention and local control households, as shown in table A3.3. The distribution of low fertility plots among sample groups may thus be driving these surprising results and suggests the need to examine differences between sample groups more closely, an exercise I leave for later work.

application having an effect statistically different from zero. Due to their low explanatory power, as well as data limitations imposed by sample size, we exclude both fertilizer application timing and phosphorus application from our analysis.

Marginal effects of weeding labor are higher on the high fertility plots than on the low across all estimations. For the OLS estimation, the marginal effect is 3.8 kg maize/day of weeding labor on the high fertility plots, and an imprecisely estimated 0.6 kg maize/day of weeding labor on the low. Interestingly, the fixed effects points estimates are larger, at 8.0 kg maize/day of weeding labor on the high fertility plots and 2.0 kg maize/day of weeding labor on the low, though the latter is not statistically different from zero. Our results for the subsample of local and distant control households are similar to those found with fixed effects estimation of the full sample for the marginal effect of nitrogen, with marginal effects 3.1 kg maize/kg N on the high plot and 7.2 kg N/kg maize on the low, and the latter is statistically different from zero. For the marginal effect of weeding labor, however, the magnitudes are reversed, and there is a higher response on the low fertility plots than the high. This is possibly due to the negative interaction between maize response to weeding labor and total C[52] and the fact that average levels of total C were higher for intervention households than for either control group.[53]

When using the control function to instrument for endogeneity of weeding labor, these effects range for nearly zero to negative, and the standard errors are larger in magnitude than the point estimates. Given the large standard errors on the control function labor estimates and the fact that the residuals from the first stage are not statistically different from zero (as shown in

[52] This can be seen for the full sample in columns (1) and (2) of table 3.3. When excluding the intervention households, as in column (3) of the same table, this relationship is positive, though imprecisely estimated.
[53] For the intervention households, the mean level of total C (%) in the soil is 1.44. For the local and distant controls, it is 1.34 and 1.24, respectively.

table 3A.2 of the appendix), it is likely that additional data are needed to accurately account for the effects of weeding labor in production function estimation.

The difference between the OLS and FE estimates again suggests bias in the OLS estimates, potentially due to differences in farmer skill and experience, or due to measurement error (including idiosyncratic overreporting of weeding labor). Given these differences and the possibility of bias arising from heterogeneity between plots and plot managers, we use the fixed effects estimates for the profitability portion of the analysis, described in greater detail in section 3.6.

Breaking down these overall effects by their specific interactions with total C and each other, we can isolate specific components of equation (3), as shown in table 3.3. We find in the OLS estimations that maize response to nitrogen increases with total C, while the relationship is negative but not statistically significant using either fixed effects or the control function approach. Across all three estimations using the full sample, we find a negative interaction between total C and maize response to weeding labor, and the relationship is statistically significant for both the OLS and the CF estimates.

Finally, using coefficients from the fixed effects estimation with the full sample and the full set of results as shown in table 3A.2 of the appendix, interactions between soil texture and nitrogen application are statistically significant and contribute to 6.7% of the overall effect of nitrogen, while the interactions between soil texture and weeding labor are not statistically different from zero. Interactions between total C and either input are large and significant in the OLS results (but noisy in the FE results), and a significant portion of the overall effect is attributable to differences in growing conditions and other plot characteristics not captured in our soil data.

Table 3.2: Marginal effects of nitrogen and weeding labor on maize yield by plot and estimator

	Pooled OLS		Fixed effects		Fixed effects (subsample)		Control function	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High plots	Low plots	High plots	Low plots	High plots	Low plots	High plots	Low plots
kg N/ha	3.478**	9.797***	2.575	6.518*	3.120	7.194**	1.617	3.913*
	(1.431)	(1.438)	(2.627)	(3.619)	(3.641)	(3.638)	(1.837)	(1.981)
Weeding days/ha	3.810**	0.649	7.971**	2.043	2.887	7.050***	0.340	-3.454
	(1.517)	(1.605)	(3.113)	(2.621)	(3.313)	(2.366)	(3.836)	(3.468)

Standard errors computed using the delta method and in parentheses below. *** p<0.01, ** p<0.05, * p<0.1

Table 3.3: Pooled OLS, plot-level fixed effects, and control function key results of determinants of maize yield

	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	Fixed effects	Fixed effects subsample	Control function
kg N/ha	-8.350	-7.455	4.838	11.06
	(6.140)	(9.011)	(13.05)	(14.19)
(kg N/ha)^2	-0.0113	0.000184	-0.0489*	-0.000262
	(0.00742)	(0.0167)	(0.0256)	(0.00603)
Weeding days/ha	14.73***	21.18***	9.676	12.40*
	(4.476)	(6.120)	(6.120)	(6.732)
(Weeding days/ha)^2	-0.0127**	-0.0207**	-0.0351***	-0.00906
	(0.00491)	(0.00937)	(0.00978)	(0.00562)
Other labor activities (days/ha)	0.373	-0.331	0.807	1.365
	(1.710)	(3.454)	(4.165)	(2.690)
(Other labor activities)^2	-0.000838	1.14e-05	-0.00115	-0.00183
	(0.00242)	(0.00545)	(0.00637)	(0.00322)
Total C (%)	560.9***			936.5**
	(157.9)			(399.6)
Interactions				
kg N/ha x Total C	3.184**	-1.622	3.600	-0.498
	(1.338)	(5.271)	(6.467)	(3.082)
kg N/ha x Weeding days/ha	-0.000326	0.00735	0.0270	-0.00683
	(0.00660)	(0.0154)	(0.0260)	(0.00652)
Total C x Weeding days/ha	-2.457***	-2.560	1.929	-3.526**
	(0.594)	(2.135)	(2.654)	(1.387)
Observations	438	438	254	218
R-squared	0.407	0.502	0.755	0.421
Number of plotid		310	178	

Robust standard errors clustered at the village level and in parentheses below. All regressions include the covariates included in table 3A.4 *** p<0.01, ** p<0.05, * p<0.1

3.6. Profitability analysis

3.6.1 Explanation of value cost ratios

While fertilizer and weeding labor increase maize yield, whether the extent to which they do so outweighs the cost of acquiring and using these inputs is another question, and it is this that we turn to next. Without the data to identify causal impact of each input, we instead use multiple price scenarios and two different measures of profitability—average value cost ratios and marginal value cost ratios—to set bounds on the range in profitability as suggested by our regression results.

The average cost value ratio (AVCR) measures whether, under a given set of prices, the change in predicted maize yield associated with using that input at observed levels justifies the cost of the input. It uses the average physical product (APP), as calculated from our regression results and observed levels of use of input *k*, and is given by $\frac{\hat{Y}_1 - \hat{Y}_0}{k}$, where $\hat{Y}_1$ denotes predicted maize yield with use of the input, $\hat{Y}_0$ predicted maize yield without, and *k* the observed quantity of the input applied. The APP is then the change in maize yield per unit of input applied relative to zero application. The APP is useful in that it gives the overall expected effect of use of an input at observed levels on maize yield, or $\frac{dy}{dk}$ in equation (3); it incorporates all interactions between the input of interest and other inputs and plot characteristics as modeled in the production function. The AVCR of an input *k* is given by:

$$AVCR_{k,eijv} = \frac{p_e^y APP^k}{p^k}$$

An AVCR of 1 indicates a break-even cost, *i.e.*, that use of that input at observed levels yields a net zero expected profit, while an AVCR greater than 1 indicates that a risk neutral household would increase its expected returns from maize through use of that input. In our context of smallholders operating in markets with limited credit access and unobserved transactions costs, it is plausible that farmers are risk averse or face costs higher than those captured in our model; we hence follow the literature (e.g., Xu et al., 2009; Sauer and Tchale, 2009; Bationo et al., 1992) and assume a risk premium of 1, so that a minimum AVCR of 2 is required for fertilizer application to be attractive to most farmers. Given the abundance of family labor and relative scarcity of unskilled work available in our study area, we do not consider labor application to be a risky endeavor; the opportunity cost of family labor is simply the value of leisure.

Conversely, the marginal value cost ratio (MVCR) measures the expected profitability of an input at the margin, or whether, at observed levels of input use, the expected change in maize yield from an additional unit of that input is profitable. The MVCR is given by:

$$MVCR_{k,eijv} = \frac{p_e^y MPP^k}{p^k}$$

Where the marginal physical product (MPP) of input *k* is its marginal effect on yield, $\frac{\partial y}{\partial k}$, as given in equation (3) and table 3.2. An MVCR of 1 indicates that, in expectations, the input is being used at its most profitable level; an MVCR<1 implies that the input is being overapplied; and an MVCR>1 implies that profits could be increased by increasing use of that input. As with AVCR, we use different price scenarios calculate the MVCR and fraction of plots above an MVCR of 1 for fertilizer application and weeding labor. For fertilizer application, we also calculate the fraction of plots above an MVCR of 2 to account for risk aversion stemming from application of a costly input with uncertain yields.

There are certain drawbacks to using value cost ratios as measures of profitability. Both the AVCR and MVCR assume independence between the prices used and physical products, though this is a reasonable assumption given the geographic homogeneity in prices and plot-level heterogeneity in physical products. They also assume that there are no other costs incurred to the farmer outside purchasing the fertilizer itself, such as an increase in labor demand. Our inclusion of an interaction between fertilizer application and weeding labor means that changes in weeding labor demand that result fertilizer application factor into the VCR calculation, but changes in demand for other activities and inputs, such as labor to apply fertilizer, do not. While estimation of a profit function would more accurately account for these additional costs, calculation of VCRs is less data-intensive—a significant benefit given our small sample.

Like many other profitability measures, value cost ratios do not account for risk aversion or non-market valuation of ensuring household food security over profit maximization, and they say nothing as to whether the money spent on fertilizer could be used more profitably elsewhere: they are measures of absolute, rather than relative profitability. However, setting a VCR threshold of 2 as the minimum for most farmers to find fertilizer use profitable *enough* allows us to incorporate more realistic aspects of a smallholder's optimization problem, such as risk aversion, more easily than through other measures, such as estimation of a profit function. Finally, value cost ratios are the measures most commonly used in the empirical literature on fertilizer profitability, allowing for direct comparison of our results to those found in other studies.

3.6.2 Explanation of price scenarios

Since we are interested in the expected profitability of fertilizer and family weeding labor under a range of conditions, we calculate AVCRs for each under three different maize price scenarios. The first uses the median price from when farmers in our sample were most likely to sell maize (June-August), to capture the price faced by the average farmer in our sample. The second scenario uses the maximum monthly average price for the growing season, as an upper limit for the highest returns a farmer could receive in that year. Given that farmers may face high transportation costs in either buying or selling maize, the third scenario uses the same maize prices as in the first but also includes transport costs. Though only 112 households reported selling maize after the 2013/14 growing season, and only 64 after the 2014/15 growing season, we calculate transport costs as though all farmers sold maize.[54] To do so, we subtract the cluster-level median transport cost paid by farmers selling maize from the appropriate maize price. Many maize sales occurred at the field, leading to very low transport costs incurred by farmers in our sample.

We use four different values for fertilizer prices. The first is the fully subsidized price of subsidized nitrogen, weighted by the average ratio of NPK to urea applied by the farmers in our study. The second scenario calculates the average price of commercial nitrogen in this area, weighted analogously. Due to heavy input subsidies provided by the Farm Input Subsidy Program (FISP), very few farmers paid full price for all of their fertilizer, though very few received only subsidized fertilizer. As such, the first scenario underestimates the prices paid by farmers, while the second scenario overestimates them. Our third fertilizer price accounts for the combination of commercial and subsidized fertilizer that farmers used by taking the median of actual price paid per kilogram of nitrogen by all farmers in our sample. This price accounts for varying levels of nitrogen in NPK and urea, and for different quantities of subsidized and unsubsidized fertilizer obtained by households. The fourth scenario adds the costs of transporting

[54] Doing so likely underestimates the average returns to farmers who did sell maize, as those who did not probably faced higher transport costs and lower expected returns, but it also simplifies the analysis and comparability with the other price scenarios. Moreover, we lack data on which households purchased maize and the costs paid to transport the purchased maize back to the farm, making it impossible to calculate maize prices for net buyers, as Sheahan et al. (2011) do.

fertilizer back to the farm to the third scenario, again accounting for potentially high costs that have been shown to ultimately affect the profitability of use (Suri 2011).[55] Median prices for each scenario are presented in table 3.4, and more detailed price information can be found in the appendix.

Finally, agricultural wage rates in Malawi differ significantly by activity and location-specific market and soil characteristics. The villages in this sample are clustered geographically, so to best capture the average wage that a farmer would expect to pay to hire in labor, we use cluster-level median wages. With 8 clusters in total, this gives 8 different weeding wages.

[55] Due to data limitations, these values were calculated from the costs farmers reported in 2014 to transport commercially purchased nitrogen back to the farm and relies on the assumption that subsidized fertilizer would be subject to comparable transport costs and that, once accounting for inflation, the costs did not change substantially from one growing season to the next.

Table 3.4: Description of price scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Med. fertilizer price (2015 MWK/kg N)	29	296	405	1158	1158
Fertilizer price description	Subsidized	Median of household-level weighted average of subsidized and unsubsidized fertilizer	Median of household-level weighted average of subsidized and unsubsidized fertilizer + transport costs	Unsubsidized	Unsubsidized
Fertilizer transport costs?	No	No	Yes	No	No
Median maize price (2015 MWK/kg maize)	123	123	121	123	250
Maize price description	Median price from months in which most households sold	Median price from months in which most households sold	Median price from months in which most households sold + transport costs	Median from months in which most households sold	Maximum before next season's harvest
Maize transport costs?	No	No	Yes	No	No
Median weeding wage (2015 MWK/day)	929	929	929	929	929

3.6.3 Profitability results

As discussed above, we use coefficients and marginal effects from the fixed effects estimation, column (2) of table 3.3, to calculate physical products and value cost ratios. Doing so allows us to focus on observable plot characteristics and input use without potential contamination of results by unobservable time-invariant heterogeneity. Using the coefficients from estimation, we calculate the predicted yield with and without fertilizer and divide the difference by observed levels of nitrogen application. As would be expected from the marginal effects results presented in table 3.2, the APP, or change in kilograms of maize per kilogram of nitrogen applied, is much higher on the low fertility plots than the high, and this translates into significant differences in fertilizer profitability. As can be seen in the descriptives in table 3.1, these differences occur despite a slightly (and statistically significantly) higher rate of fertilizer application on the low fertility plots than the high. The range in and magnitude of AVCRs of fertilizer are similar to those found by Sheahan et al. (2013) in Kenya, who estimated AVCRs between 0.5 and 6.1, with differences by geographical location and soil type. The one exception is for the fully subsidized fertilizer case, scenario 1, which is to be expected given the low price of subsidized fertilizer.

As shown in table 3.5, price scenario 1 indicates the expected profitability of fertilizer use if it were fully subsidized, using the subsidy prices for the 2014/2015 growing season (500 MWK/50 kg bag of fertilizer, or slightly over $1 per 50 kg bag). At these low prices, fertilizer is profitable on every plot where the APP of fertilizer was non-negative.[56] This translates to 63.3% of high fertility plots and 70.8% of low fertility plots in the sample which had AVCRs exceeding 1. Unsurprisingly, these numbers are fairly consistent with the AVCR cutoff is raised to 2; the

[56] The APP of fertilizer was negative on 62 of the high fertility and 57 of the low fertility plots, the latter of which is surprising, given the relatively high APP and MPP of fertilizer on these plots.

subsidized price of fertilizer is low enough that, for plots on which the predicted yield increases with fertilizer use, it remains profitable even with the risk premium of 1.

Price scenario 2 represents the price faced by the average household in our sample, by cluster, by using median maize prices from the months in which farmers were most likely to sell and a weighted average of subsidized and commercial nitrogen for its fertilizer price. Yet at these prices fertilizer application at observed levels was not profitable for a risk neutral farmer on 44% of plots. Between plots, there is significant variation: 63.4% of low fertility plots crossed the break-even threshold of 1, while only 46.9% of high fertility plots did. At these prices, fertilizer application is only attractive for a risk averse farmer on 31.1% of high fertility plots and 59.9% of low fertility plots—and on only 46.4% of the plots overall—as seen when the AVCR threshold is raised to 2. When accounting for transport costs of fertilizer and maize, as in scenario 3, only 7.3% of high fertility plots and 29.9% of low fertility plots cross this threshold for the risk averse farmer. This drop is likely due to the costs incurred in transporting fertilizer back to the farm, given the low costs of transporting maize to the point of sale, as shown in table 3.4.

Table 3.5: Plot-level 2015 fertilizer APP, AVCR, and % of plots with AVCR above threshold

		High plots	Low plots	Both plots
	APP (median)	2.33	8.2	3.42
Median AVCR	Scenario 1	9.47	32.7	15.1
	Scenario 2	0.86	3.26	1.68
	Scenario 3	0.75	2.59	1.22
	Scenario 4	0.24	0.91	0.38
	Scenario 5	0.48	1.91	0.72
% with AVCR>1	Scenario 1	63.3	70.8	67.3
	Scenario 2	46.9	63.4	55.7
	Scenario 3	18.4	33.9	26.3
	Scenario 4	2.8	48.5	27.2
	Scenario 5	37.3	64.7	51.1
% with AVCR>2	Scenario 1	63.3	68.8	66.2
	Scenario 2	31.1	59.9	46.4
	Scenario 3	7.3	29.9	18.7
	Scenario 4	0	5.0	2.6
	Scenario 5	2.8	49.5	27.7
# of plots		155	155	310

Table 3.5 also shows that if farmers are to continue to apply fertilizer at current levels in absence of a subsidy, maize response to fertilizer must increase. Scenario 4 uses commercial fertilizer prices and the same maize prices as in scenarios 1-4: the average from the months in which farmers in this survey were most likely to sell maize. Only 2.6% of plots in all had a high enough AVCR for a farmer with a risk premium of 1 and selling at this time of year to find fertilizer application at observed levels to be profitable; for a risk neutral farmer, only 27.2% of plots showed high enough returns. Even under the most favorable maize prices, as in scenario 5, fertilizer application would not be profitable on 62.7% of high fertility plots and 35.3% of low fertility plots, while this number rises to 97.2% of high fertility plots and 50.5% of low fertility plots for farmers with a risk premium of 1. Moreover, as mentioned previously, neither the AVCR nor the MVCR account for the costs associated with expected changes in use of other

inputs, such as additional labor required to apply fertilizer. As such, the AVCRs presented above likely overestimate the actual expected returns to using fertilizer.

While average value cost ratios show the change in predicted yield per unit of input applied, holding constant use of other inputs, marginal value cost ratios give the change per *last* unit of input applied. Given the decreasing marginal returns to fertilizer as shown in table 3.3, we would expect that MPPs be lower than APPs, and this is indeed the case for the low fertility plots. Table 3.6 gives results of the same analysis in table 3.5 but using marginal values. The MPPs are the marginal effects shown for fixed effects estimation of the full sample in table 3.3, and there is more variation between plots than there was for the APPs. The range in and magnitude of MPP is again similar to that found by Sheahan et. al (2013), though significantly lower than that found by Marenya & Barrett (2009), also in Kenya. While Marenya & Barrett's study is more comparable to ours in that it explicitly accounts for the effect of SOC on fertilizer profitability, fertilizer application rates are significantly lower in their sample, with only 3% of plots receiving at least 20 kg N/ha.

The price scenarios reflect great heterogeneity in whether observed levels of fertilizer application are, in expectation, profitable at the margin: depending on the prices faced by farmers, fertilizer is either overapplied, underapplied, or applied at optimal rates. In price scenario 1, where farmers face fully subsidized fertilizer prices, fertilizer is underapplied on every plot, as the MVCR exceed 2 on all plots.

In scenario 2, which uses a weighted average of subsidized and unsubsidized fertilizer prices, the median MVCR of 0.77 on the high fertility plots indicate an *overapplication* for a risk-neutral farmer, as highlighted by fertilizer is applied at most profitable levels on only 44.7% of these plots. Conversely, the median MVCR of 1.95 and corresponding 99.6% of low fertility plots with an MVCR exceeding 1 implies that fertilizer is *underapplied* on these plots. Once accounting for transport costs, as in scenario 3, the median MVCRs drop slightly—to 1.78 on the high fertility plots and 1.67 on the low, but the decrease in fraction of plots on which fertilizer is overapplied is considerably lower. Once accounting for transport costs, fertilizer is applied beyond most profitable levels on 56.6% of high fertility plots and 35.8% of low fertility plots.

Table 3.6: Median 2015 fertilizer MPP, MVCR, and % of plots with MVCR above threshold by plot

		High plots	Low plots	Both plots
	MPP (median)	2.57	6.52	4.56
Median MVCR	Scenario 1	11.9	27.7	16.8
	Scenario 2	0.77	1.95	1.95
	Scenario 3	0.70	1.78	1.67
	Scenario 4	0.27	0.74	0.63
	Scenario 5	0.56	1.41	1.11
% with MVCR>1	Scenario 1	100	100	100
	Scenario 2	44.7	99.6	72.4
	Scenario 3	14.8	56.6	35.8
	Scenario 4	0	0	0
	Scenario 5	0	100	50.5
% with MVCR>2	Scenario 1	100	100	100
	Scenario 2	35.5	48.4	42.0
	Scenario 3	12.4	19.0	15.8
	Scenario 4	0	0	0
	Scenario 5	0	0	0

If farmers sold maize at the same time but were only applying commercial fertilizer, fertilizer would be *overapplied* on every plot, as shown by the fact that 0% of plots cross the break-even MVCR threshold of 1. Finally, scenario 5, in which farmers do not use subsidized fertilizer but are able to hold off on selling maize until shortly before the next harvest, shows a wide range in the profitability of observed levels of fertilizer application for the risk-neutral farmer—with all low fertility plots and zero high fertility plots crossing the break-even threshold of 1—but that risk-averse farmers would benefit from a decrease in fertilizer on all plots.

Interpretation of weeding labor results, presented in tables 3.7 and 3.8, requires some additional assumptions.[57] First, in pooling family and hired labor, we implicitly assume that the two produce equal returns and are valued at equal rates. While these assumptions are likely too strong—Frisvold (1994) and others have shown that family labor often produces different returns than does hired and that it may also be valued differently—we are unable to disaggregate or test for substitution between the two different types of labor, given the low levels of hired in labor in this sample. In fact, we find that the mean days of hired in weeding labor are not statistically different between plots, at 5.2 days/ha on the most fertile and 6.7 days/ha on the least.

Moreover, given the abundance of family agricultural labor in this area, a market weeding wage is likely higher than the shadow wage by which household labor is valued. If this is the case, our weeding labor AVCRs are underestimates, since the "true" cost of labor application is lower than the values we use. In a similar vein, measurement error becomes a concern in assessing weeding labor profitability. If weeding labor is overreported, our results will underestimate returns to weeding labor. Relatedly, since we are unable to disentangle whether a given rate of weeding was in response to the number of weeds on the plot or other factors, our sample may contain plots that were inadequately weeded, thus resulting in underestimates.

With this in mind, we do find variation in APPs between plots, with a median change in expected maize yield of 10.0 kg maize/day of weeding labor on the high fertility plots, and 6.49 kg maize/day on the low, though we cannot conclude whether this means that weeding labor is

[57] These tables exclude scenarios 1 and 4, which are identical to scenario 2 for weeding labor VCRs.

more effective on more fertile plots. Since neither hired nor family weeding labor application is statistically different between plots, we can conclude that the gap in weeding labor APPs, while smaller than that found for fertilizer APP, cannot be attributed to differences in labor application rates.

The variation in APPs translates into a gap in AVCRs and fraction of plots which cross the AVCR break-even point of 1. In scenario 2, observed levels of weeding labor application sufficiently increase maize yield on 74.7% of high fertility plots but on only 41.1% of low fertility plots. Unsurprisingly, given the low maize transport costs shown in table 3.4, accounting for these costs, as in scenario 3, does little to affect the AVCRs of weeding labor. If farmers are able to wait to sell their maize until it reaches the maximum price for the growing season, as in scenario 5, these numbers rise to 89.9% on the high fertility plots but still only 77.8% on the low.

Table 3.7: Plot-level 2015 weeding labor APP, AVCR, and % of plots with AVCR above threshold

		High plots	Low plots	Both plots
	APP (median)	10.0	6.49	7.62
Median AVCR	Scenario 2	1.34	0.87	1.14
	Scenario 3	1.31	0.85	1.12
	Scenario 5	2.56	1.64	2.13
% with AVCR>1	Scenario 2	74.7	41.1	57.8
	Scenario 3	73.3	38.0	55.5
	Scenario 5	89.9	77.8	83.8

We find the same pattern of results in marginal physical products, at 7.97 kg maize/day of weeding labor on the high fertility plot and 2.04 kg maize/day on the low. Accordingly, fertility plots are more likely to benefit from a decrease in weeding labor than the high fertility plots. In fact, at market wages, observed levels of weeding labor surpassed the most profitable level on all low fertility plots for farmers selling directly after harvest, even assuming maize sales occurred directly at the field and that the farmer thus incurred no transport costs. Even for those selling when maize had reached its maximum market price, observed weeding levels were, in terms of expected profits, too low on only 10.4% of low fertility plots, as compared to 100% of the high.

Table 3.8: Median 2015 weeding labor MPP, MVCR, and % of plots with MVCR>1 by plot

		High plots	Low plots	Both plots
	MPP (median)	7.97	2.04	4.98
Median MVCR	Scenario 2	1.15	0.30	0.46
	Scenario 3	1.12	0.29	0.44
	Scenario 5	2.14	0.55	1.0
% with MVCR>1	Scenario 2	68.7	0	34.0
	Scenario 3	67.7	0	33.6
	Scenario 5	100	10.4	54.8

3.7 Classifications of most and least fertile plots

How did farmers assess plot fertility? This section exploits the survey design to explore the degree to which farmers' rankings of their most and least fertile plots corresponds to observed measures of plot fertility, which is of particular interest, given that our objectively more fertile plots realized lower returns to fertilizer than did the least fertile plots, while average yields were not statistically different. Doing so builds on recent work suggesting that farmers' reports of soil type but not soil quality correspond to various soil fertility measures in Kenya and that farmers' perceptions of soil quality are correlated with crop yield (Berazneva et al. 2018).

First, table 3.9 shows average levels of total C, clay, and silt, as well as average yields, by plot and fertility definition. It also shows the frequency with which subjectively-defined high fertility plots had lower values on each of these measures than the low fertility plots. Across all measures, between 24% and 43% of households did so. Surprisingly, this also held for the 2013/14 growing season yields, which occurred shortly before farmers were first asked to identify their plots accordingly, suggesting that many farmers did not do so on the basis of short-term production. Instead, it is possible that farmers are identifying plot fertility according to average yields, which is supported by the fact that a lower fraction of households "misclassified" the high fertility plots according to average yields, though with so few households planting maize on both plots and in both years it is difficult to say anything definitively.

It is possible that they are instead doing so according to productivity, i.e., according to which plot obtains the highest yield response to inputs. To explore this further, we re-estimate equation (4) again using plot fixed effects but instead follow farmers' definitions of their most and least fertile plots. We also re-estimate (4) for the subsample of plots on which farmers' ranking corresponded to the plots' relative total C levels. That is, this restricted sample includes plots on which a farmer's high fertility plot had higher levels of total C than his or her low fertility plot.[58]

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[58] Doing so disproportionately excludes distant control households. Of households which grew maize on both plots in a given year, which are those included in columns (5) and (6) of table 3.10, 37% of distant control households "misclassified" plots on the basis of total C, while 33% of local controls and 27% of intervention households did. It also disproportionately excludes households in Kandeu (with 52% "misclassifying"), then Mtakataka (40%), and Nsipe (34%). 22% of households in Golomoti and 11% in Linthipe, again restricting the sample to households which grew maize on both plots in the same year, did.

Table 3.9: Average total C, clay, silt, and yields by plot and fertility classification

Fertility measure	Objective classification		Subjective classification		% of HHs in subsample "misclassifying" fertility	
	High plots (1)	Low plots (2)	High plots (3)	Low plots (4)	% of HHs in subsample (5)	# of HHs in subsample (6)
Total C (%)	1.82***	0.88	1.44***	1.24	34.2%	123
	(0.54)	(0.22)	(0.66)	(0.57)		
Clay (%)	33.4***	26.1	29.63	29.91	43.1%	123
	(19.6)	(16.3)	(17.09)	(19.75)		
Silt (%)	13.8	11.2	12.59	12.41	39.0%	123
	(15.9)	(16.1)	(15.79)	(16.42)		
Yield (2014)	1597.5**	1969.3	2001.5***	1528.9	37.3%	59
	(1130.7)	(1516.7)	(1500.3)	(1097.9)		
Yield (2015)	1355.3	1357.0	1567.2***	1115.3	28.9%	83
	(942.1)	(1009.4)	(1045.0)	(828.6)		
Yield (2014 and 2015 average)	1472.5	1650.7	1777.9***	1312.9	24.1%	29
	(1042.3)	(1311.4)	(1301.7)	(986.3)		
# of plots	155	155	145	165		

Note: Standard deviations in parentheses below. *** denotes high fertility plots different from low fertility plots, using the corresponding fertility classifications, at p<0.01, ** denotes the same for p<0.05, and * denotes the same for p<0.1. Differences in number of plots between columns (1) and (2) are due to trimming, described in greater detail below. In columns (5) and (6), yield results only include households which cultivated maize on both plots in the corresponding year, while soil characteristics only include households with soil data for both plots.

Table 3.10: Plot-level fixed effects marginal effects of nitrogen and weeding labor on maize yield by plot and classification of plot fertility

	Objective classification Full sample		Subjective classification Full sample		Subjective classification Subsample	
	(1)	(2)	(3)	(4)	(5)	(6)
	High plots	Low plots	High plots	Low plots	High plots	Low plots
kg N/ha	2.575	6.518*	5.599**	5.282**	9.512**	4.289
	(2.627)	(3.619)	(2.714)	(2.538)	(3.927)	(3.523)
Weeding days/ha	7.971**	2.043	4.598*	3.118	1.367	-2.925
	(3.113)	(2.621)	(2.604)	(2.218)	(2.801)	(2.627)
Number of plots	155	155	165	145	81	81

Notes: As in the main analysis, the objective classification groups plots at the 50th percentile of total C levels across the entire distribution. The farmer-identified subsample excludes households where the farmer-identified high fertility plot had lower levels of total C than that same household's self-identified low fertility plot. The subsample also necessarily excludes households for which yield data was not collected on one of the two plots, due to maize not being planted in that growing season, while the full sample does not exclude such households. All regressions include the same covariates as in the main part of the analysis.

As shown in columns (3) and (4) of table 3.10, the difference between the marginal effects of nitrogen and weeding labor is much smaller between the subjectively defined plots than when using the objective classifications. This is unsurprising, given the share of plots which were "misclassified" based on the observable factors described in table 3.9 above. Interestingly, when excluding these plots, as in columns (5) and (6), the range widens for the marginal effect of nitrogen. When farmers' identification of their high fertility plot corresponded to higher levels of total C, maize response to nitrogen was higher on the high fertility plot, at 9.51 kg maize/kg N than the low, at 4.3 kg maize/kg N.[59]

Together, this suggests that there are certain factors that affect the profitability of input use that are not captured in our model, even with the extensive controls provided by plot-level

[59] This is not primarily attributable to differences in fertilizer application rates. Using the subjective classifications of plots, there is no statistically significant difference in fertilizer application rates between the high and low fertility plots, at 64.5 kg N/ha on the high plots and 69.1 kg N/ha on the low. With the subsample of farmer-ranked plots, where soil carbon levels on the high fertility plot exceeded the low, the differences in fertilizer application rates are larger—with an average of 65.1 kg N/ha on the high fertility plots and 54.8 kg N/ha on the low—but are not statistically different.

fixed effects. These factors could be biological in nature, such as water access, or it could simply be that total C is, in our setting, a poor proxy for soil fertility. Alternatively, there could be behavioral factors that affect input productivity and yields. For example, farmers may prioritize application of fertilizer on their self-identified high fertility plots, thereby applying it at recommended times, while application on the low fertility plot is delayed.[60] This could result in higher returns to fertilizer and higher yields on the farmer-identified high fertility plots, resulting in a self-fulfilling prophecy of sorts. Furthermore, on plots "correctly" identified plots, these behavioral differences, combined with biological factors (higher levels of total C on "correctly" identified high fertility plots), could result in the pattern of results observed in table 3.10. Understanding whether this is the case and the degree to which potential behavioral biases resulting from farmers' perceptions of their plot fertility affect yields and returns to input use is an important next step for further research.

[60] In the 2014/15 growing season, farmers (excluding those who applied fertilizer in March) reported applying NPK to their own-identified low fertility plots on average roughly two additional days after planting than they did on the high fertility plots (NPK was applied on average 1.6 weeks after planting on the high fertility plots and 1.9 weeks after planting on the low). For urea application, this difference was roughly 1 additional day after planting on the low fertility plots (it was applied 4.4 weeks after planting on the high fertility plots and 4.5 weeks after planting on the low). These differences are small, but our coarse measures do not account for the timing of rainfall or other factors that would affect maize response to fertilizer, and we conclude that additional data is needed to examine this question in greater depth.

3.8 Conclusion

While previous studies have discussed heterogeneity in maize response to inputs, evidence on heterogeneity within households remains limited. This study begins to fill this gap by examining maize plots identified by farmers as their most and least fertile to show the range in maize response to inputs found within households and villages. In doing so, several policy-relevant conclusions emerge.

First, the physical products—and hence profitability—of fertilizer and weeding labor vary depending on plot characteristics and interactions with each other. We find that, even while controlling for unobserved plot characteristics that impact fertility, 6.7% of the overall effect of inorganic nitrogen application on maize yield can be attributed to soil texture, while the interactions between soil carbon and nitrogen application is large but imprecisely estimated. The overall contribution of soil carbon and texture in explaining maize response to weeding is not statistically different from zero, which is unsurprising given the importance of soil characteristics in nitrogen uptake. As discussed previously, our methods of aggregating both nitrogen application and weeding labor may suppress variation in maize response rates due to timing of application or weeding, as well as differences in nutrient content of different fertilizer types and quality of labor provided by different types of laborers, so these estimates should be interpreted with caution.

Our findings of differentials in maize response to inputs by soil and plot characteristics translates into disparities in profitability of input use. We find that an increase in fertilizer application rates would increase profits on all plots, but, without the subsidy, fertilizer is *overapplied* on all plots for farmers selling directly after harvest. Similarly, the most fertile plots in our sample were more likely to benefit from an increase in weeding labor rates, despite comparable rates of weeding labor applied to both categories of plots. Moreover, the heterogeneity in crop response rates persists within households, implying that this variation is not due solely to farmer skill and other unobserved household characteristics.

We also find that maize response to both weeding labor and nitrogen application decreases with the quantity of total C in the soil, though the interactions are imprecisely estimated. That the relationship between total C and fertilizer response rates would be negative is unexpected, as a study in Kenya found a positive relationship over a range of medium to high soil C (Marenya & Barrett 2009). At the same time, other studies are consistent with a threshold yield response to soil C status, with negative or no response observed below about 0.7 to 1% (Kurwakumire et al. 2015; Zingore et al. 2007). Further work is needed to explore threshold effects of SOC on nitrogen response rates—both to identify the level of the turning point and to examine inputs and agronomic practices which can build up levels of SOC.

Finally, we found that, when using farmers' own classification of their most and least fertile maize plots, and when excluding households for which farmers' relative ranking of fertility did not correspond to an objective measure of total organic carbon, the marginal physical product of fertilizer was significantly higher on the high fertility plots than on the low. This suggests that there are important unobserved variables, such as farmer effort, that potentially bias estimates of input physical products.

Our results across all three estimations point to the important roles of complementary input markets and highlights the linkages between soil characteristics, labor markets, fertilizer profitability, and maize yield. In particular, the finding that weeding labor is overapplied on many plots can be attributed to a number of factors, including underdeveloped rural labor markets, where a scarcity of employment opportunities leads to low valuation of family labor.

The increase in profitability of input use when farmers are able to hold off on selling maize until prices have increased suggest the need for policies such as improved storage options and development of rural labor markets for additional sources of income which allow farmers to wait to sell. Moreover, the range we find in maize response to fertilizer and weeding labor based off of plot characteristics suggests that blanket recommendations aimed at increasing fertilizer application rates are unlikely to be effective without policies which help improve soil fertility or address constraints in use of complementary inputs.

APPENDIX

Table 3A.1: Summary statistics of variables by plot, years pooled

	High plots				Low plots			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Plot-level inputs and output								
Maize yield (kg/ha)	1472.5	1042.3	63.7	5867.4	1650.7	1311.4	109.3	5945.6
kg N/ha	59.1	61.1	0	289.7	74.1	77.9	0	393.8
Total weeding days/ha	130.0	108.2	5.4	491.3	132.6	110.4	0	498.6
Other labor activities (days/ha)	174.8	122.0	5.4	565.1	174.9	118.2	13.6	578.8
Hybrid maize seed (1=yes)	0.35	0.48	0	1	0.45	0.50	0	1
Soil characteristics								
Total C (%)	1.82	0.53	1.27	4.32	0.89	0.21	0.44	1.27
% clay in soil	33.0	19.2	7.6	87.6	26.7	16.4	5.6	87.6
% sand in soil	53.3	23.0	2.6	86.6	62.7	20.7	2.6	88.4
Plot characteristics								
Plot area (ha)	0.27	0.20	0.05	0.99	0.26	0.18	0.05	0.97
Moderate or steep slope	0.12		0	1	0.10		0	1
Plot flooded in 2015 (1=yes)	0.11		0	1	0.11		0	1
Time and location controls								
Planted in November	0.23		0	1	0.24		0	1
Planted in December	0.62		0	1	0.63		0	1
Planted in January	0.15		0	1	0.13		0	1
EPA								
Linthipe local	0.30		0	1	0.02		0	1
Linthipe distant	0.04		0	1	0.10		0	1
Golomoti local	0.03		0	1	0.23		0	1
Golomoti distant (Mtakataka)	0.05		0	1	0.10		0	1

Table 3A.1 (cont'd)

	High plots				Low plots			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Kandeu local	0.12		0	1	0.17		0	1
Kandeu distant	0.12		0	1	0.01		0	1
Nsipe local	0.27		0	1	0.24		0	1
Nsipe distant	0.06		0	1	0.14		0	1
Year								
2014	0.48		0	1	0.48		0	1
2015	0.52		0	1	0.52		0	1
# observations	217				221			

Table 3A.2: Determinants of maize yield by estimator

VARIABLES	(1) Pooled OLS	(2) Fixed effects	(3) Fixed effects Subsample	(4) Control function
Plot-level inputs				
Kg N/ha	-8.350	-7.455	4.838	11.06
	(6.140)	(9.011)	(13.05)	(14.19)
$(\text{kg N/ha})^2$	-0.0113	0.000184	-0.0489*	-0.000262
	(0.00742)	(0.0167)	(0.0256)	(0.00603)
Weeding days/ha	14.73***	21.18***	9.676	12.40*
	(4.476)	(6.120)	(6.120)	(6.732)
$(\text{Weeding days/ha})^2$	-0.0127**	-0.0207**	-0.0351***	-0.00906
	(0.00491)	(0.00937)	(0.00978)	(0.00562)
Other labor activities (days/ha)	0.373	-0.331	0.807	1.365
	(1.710)	(3.454)	(4.165)	(2.690)
$(\text{Other labor activities})^2$	-0.000838	1.14e-05	-0.00115	-0.00183
	(0.00242)	(0.00545)	(0.00637)	(0.00322)
Hybrid maize seed (1=yes)	219.1**	202.5	-27.73	350.8***
	(97.60)	(186.6)	(182.2)	(112.2)
Plot area (ha)	255.8	-731.9	-2,081*	433.2*
	(267.9)	(755.3)	(1,059)	(236.1)
Plot and soil characteristics				
Total C	560.9***			936.5**
	(157.9)			(399.6)
% clay in soil	1.530			-2.974
	(6.543)			(8.353)
% sand in soil	-1.043			3.441
	(5.669)			(9.551)
Low fertility plot	346.8			948.2**
	(272.1)			(370.8)
Plot flooded in 2015 (1=yes)	377.8			571.5*
	(226.0)			(293.3)
Moderate or steep slope of plot	444.7*	65.55	-359.1	320.8
(1=yes)	(256.0)	(530.3)	(736.1)	(347.2)
kg N/ha interactions				
Kg N/ha x Total C	3.184**	-1.622	3.600	-0.498
	(1.338)	(5.271)	(6.467)	(3.082)
Kg N/ha x weeding days/ha	-0.000326	0.00735	0.0270	-0.00683
	(0.00660)	(0.0154)	(0.0260)	(0.00652)

Table 3A.2 (cont'd)

	(1) Pooled OLS	(2) Fixed effects	(3) Fixed effects Subsample	(4) Control function
Kg N/ha x % clay	0.149***	0.193**	-0.0180	-0.0890
	(0.0434)	(0.0805)	(0.135)	(0.180)
Kg N/ha x % sand	0.133***	0.114**	0.144**	-0.111
	(0.0463)	(0.0511)	(0.0586)	(0.161)
kg N/ha x plot flooded in 2015	6.089**	8.707**	26.32***	7.633**
	(2.769)	(4.146)	(7.147)	(3.562)
Weeding labor interactions				
Weeding days/ha x Total C	-2.457***	-2.560	1.929	-3.526**
	(0.594)	(2.135)	(2.654)	(1.387)
Weeding days/ha x sloped plot	-3.494***	-4.511*	-4.195	-6.342***
	(1.215)	(2.398)	(2.552)	(1.176)
Weeding days/ha x % clay	-0.0750**	-0.0612	-0.0129	-0.0180
	(0.0298)	(0.0643)	(0.0621)	(0.0418)
Weeding days/ha x % sand	-0.0257	-0.0380	-0.0305	0.00569
	(0.0296)	(0.0370)	(0.0429)	(0.0394)
Weeding days/ha x plot flooded in 2015	-3.854***	-2.985	-4.790	-3.840***
	(1.099)	(2.547)	(3.081)	(1.247)
Plot x year x input interactions				
Kg N/ha x high fertility plot x 2015	-6.898**	-5.518	-26.16***	
	(2.480)	(4.102)	(7.494)	
Kg N/ha x low fertility plot x 2014	7.734**	8.562**	3.870	
	(3.006)	(4.193)	(5.213)	
Kg N/ha x low fertility plot x 2015	-1.896	-5.867	-21.88***	1.869
	(2.214)	(4.728)	(8.359)	(2.824)
Weeding days/ha x low fertility	0.483	0.00148	4.147	
plot x 2014	(1.049)	(2.659)	(2.824)	
Weeding days/ha x low fertility	-3.032	-7.356*	4.980	
plot x 2014	(3.007)	(4.269)	(4.377)	
Weeding days/ha x low fertility	-2.798*	-4.600	7.480	-3.821**
plot x 2015	(1.390)	(4.079)	(4.576)	(1.467)

Table 3A.2 (cont'd)

	(1) Pooled OLS	(2) Fixed effects	(3) Fixed effects Subsample	(4) Control function
Month planted x year, EPA x year controls				
Planted in November 2014	-456.7	-2,568***	-1,985***	
	(438.1)	(636.0)	(680.7)	
Planted in November 2015	-109.0	-1,535	487.3	-580.4**
	(432.5)	(1,047)	(1,356)	(235.9)
Planted in December 2014	-197.1	-1,723***	-872.9	
	(356.9)	(651.5)	(747.2)	
Planted in December 2015	265.1	-827.4	942.7	-7.636
	(442.7)	(827.5)	(998.2)	(115.5)
Planted in January 2015	316.0	-495.3	914.8	
	(463.1)	(704.7)	(1,011)	
Linthipe local x 2015	-553.0***	-1,660***	-1,891***	
	(182.3)	(577.5)	(559.9)	
Linthipe distant x 2014	392.2**	935.2*	1,748***	
	(176.9)	(541.9)	(453.3)	
Linthipe distant x 2015	589.5***			1,206***
	(158.7)			(236.0)
Golomoti local x 2014	88.40	1,699***	2,611***	
	(303.7)	(574.8)	(562.3)	
Golomoti local x 2015	-1,072***			-536.1*
	(183.1)			(286.3)
Golomoti distant (Mtakataka) x 2014	-88.56	882.5	1,471***	
	(209.3)	(619.8)	(537.9)	
Golomoti distant (Mtakataka) x 2015	-449.8**			85.20
	(214.9)			(272.1)
Kandeu local x 2014	313.6	1,869***	2,598***	
	(196.3)	(560.9)	(601.6)	
Kandeu local x 2015	-815.9***			-180.8
	(180.8)			(182.4)
Kandeu distant x 2014	-336.9	804.0	2,145**	
	(233.3)	(688.4)	(1,018)	
Kandeu distant x 2015	-1,149***			-801.4***
	(228.1)			(271.5)

Table 3A.2 (cont'd)

	(1) Pooled OLS	(2) Fixed effects	(3) Fixed effects Subsample	(4) Control function
Nsipe local x 2014	-347.2*	1,435***	1,736***	
	(168.7)	(500.6)	(541.4)	
Nsipe local x 2015	-980.1***			-373.2*
	(199.5)			(208.0)
Nsipe distant x 2014	-417.1			
	(247.0)			
Nsipe distant x 2015				515.0**
				(229.9)
Residuals from first stage				-0.0141
				(3.190)
Constant	-48.23	1,723**	549.3	-1,166
	(666.4)	(815.8)	(1,132)	(1,299)
Observations	438	438	254	218
R-squared	0.407	0.502	0.755	0.421
Number of plotid		310	178	

Notes: Standard errors clustered at the village level and in parentheses below. *** p<0.01, ** p<0.05, * p<0.1

Table 3A.3: Mean inputs, outputs, and plot and soil characteristics by sample group

	Sample group			p-values of differences between sample groups		
	Intervention households	Local controls	Distant controls	Intervention + local controls	Intervention + distant controls	Local + distant controls
2014 Yield (kg/ha)	2102.0[A]	1663.5	1509.8	0.16	0.50	0.06
	(1439.2)	(1161.5)	(1305.4)			
2015 Yield (kg/ha)	1253.1	1137.8	1721.2	0.39	0.05	0.07
	(836.7)	(808.8)	(1194.9)			
2014 and 2015 Avg. yield (kg/ha)	1636.0	1391.7	1610.8	0.12	0.80	0.03
	(1222.1)	(1027.1)	(1256.0)			
Kg N/ha	74.1	70.0	53.6	0.65	0.00	0.01
	(76.0)	(69.5)	(61.0)			
Weeding days/ha	123.9	137.4	136.1	0.23	0.17	0.90
	(96.7)	(116.9)	(117.5)			
Other labor days/ha	168.6	180.6	178.3	0.34	0.29	0.84
	(110.0)	(135.8)	(118.0)			
Total C (%)	1.44	1.34	1.22	0.36	0.00	0.02
	(0.69)	(0.54)	(0.54)			
% clay in soil	34.3	29.3	21.5	0.04	0.00	0.00
	(18.8)	(16.7)	(14.5)			
% sand in soil	51.7	60.2	64.6	0.06	0.00	0.02
	(22.1)	(19.9)	(22.4)			
Plot area (ha)	0.28	0.25	0.26	0.26	0.05	0.63
	(0.20)	(0.20)	(0.17)			
Moderate or steep slope (1=yes)	0.05	0.03	0.25	0.36	0.00	0.00
	(0.22)	(0.16)	(0.43)			
Plot flooded in 2015 (1=yes)	0.20	0.20	0.25	0.97	0.56	0.55
	(0.40)	(0.40)	(0.43)			

Notes: Standard deviations in parentheses below.

Table 3A.4: Selected results of fixed effects estimation of treatment effects by control group definition and inputs tested

VARIABLES	(1) Testing kg N/ha and weeding labor	(2) Testing just kg N/ha	(3) Testing just weeding days/ha	(4) Testing kg N/ha and weeding labor	(5) Testing just kg N/ha	(6) Testing just weeding days/ha
Control HH x kg N/ha	-3.843	-3.079		1.916	4.200	
	(5.520)	(5.618)		(4.899)	(4.785)	
(Year=2015) x kg N/ha	-8.309**	-8.244**		-5.511	-5.397	
	(3.499)	(3.410)		(4.670)	(4.264)	
Control x 2015 x kg N/ha	-6.421	-7.453		-16.30**	-14.81**	
	(8.925)	(9.130)		(7.256)	(7.207)	
Control HH x weeding	2.775		3.408	4.804		4.861
days/ha	(4.885)		(4.963)	(3.274)		(3.096)
(Year=2015) x weeding	1.042		0.738	-0.340		-0.663
days/ha	(2.280)		(2.475)	(3.222)		(3.617)
Control HH x 2015 x weeding	-2.443		-3.025	3.049		1.542
days/ha	(4.627)		(4.831)	(3.881)		(4.046)
Year=2015 (1=yes)	-1,754**	-1,669**	-2,548***	-1,897**	-1,844**	-2,479***
	(736.2)	(694.4)	(674.0)	(830.7)	(768.5)	(735.0)
Control HH x 2015	-1,976**	-1,904***	-1,626*	-326.5	-1,024*	618.1
	(792.8)	(706.5)	(828.2)	(710.2)	(552.7)	(662.8)
Control group definition	Distant controls	Distant controls	Distant controls	Local and distant controls	Local and distant controls	Local and distant controls
Observations	438	438	438	438	438	438
R-squared	0.468	0.466	0.398	0.521	0.479	0.428
Number of plotid	310	310	310	310	310	310

Notes: Includes all covariates from main regressions. Robust standard errors clustered at the village level and in parentheses, *** p<0.1, **p<0.05, *p<0.1

Table 3A.5: Median wages, fertilizer prices, and maize prices in 2015 MWK by EPA and cluster

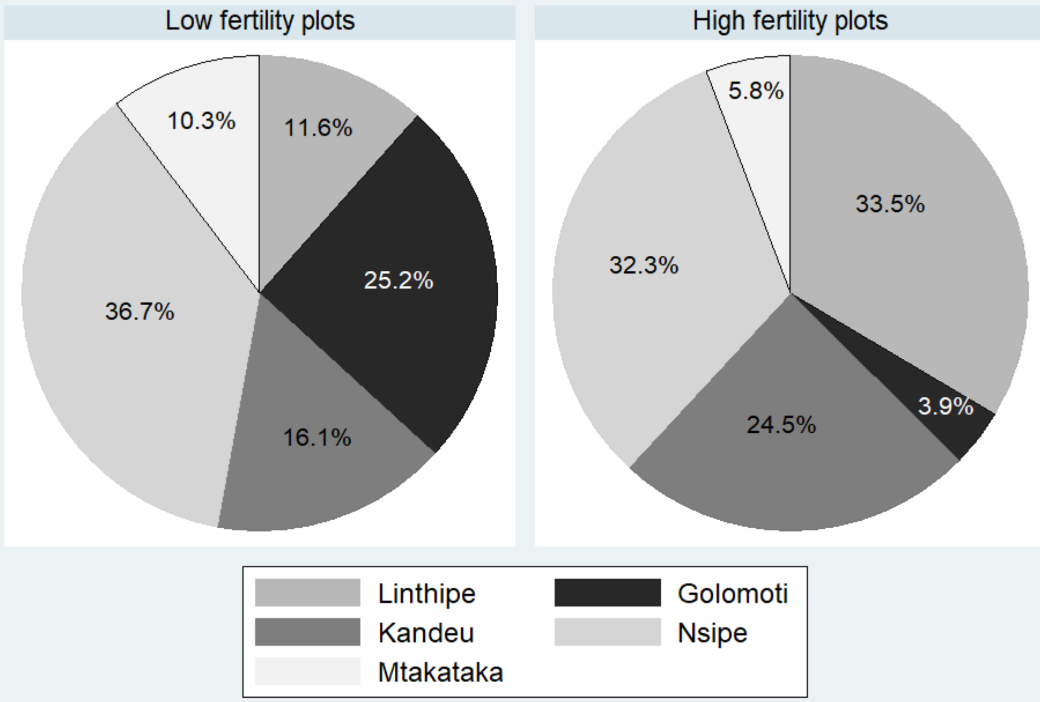
EPA	Cluster	Weeding wage (MWK/ person/day)	Nitrogen prices (MWK/kg N)	Minimum maize prices (MWK/kg maize)	Median maize prices (MWK/kg maize)	Maximum maize prices (MWK/kg maize)	AMIS market match
Linthipe	Intervention	708	1087	77	115	248	Chimbiya, Tete
	Controls	500	1152	73	114	246	Chimbiya
Golomoti/ Mtakataka	Intervention	667	1044	95	127	282	Mtakataka, Bembeke
	Controls	667	1207	95	127	282	Mtakataka
Kandeu	Intervention	1217	1180	82	128	201	Sharpe Valley, Ntcheu
	Controls	1072	1261	82	128	201	Sharpe Valley, Ntcheu
Nsipe	Intervention	929	1158	85	133	250	Ntcheu, Ntonda
	Controls	1458	1185	85	133	250	Ntcheu, Ntonda

Table 3A.6: Median transport costs in 2015 MWK by EPA and cluster

EPA	Cluster	Nitrogen transport cost (MWK/kg N)	Maize transport cost (MWK/kg maize)
Linthipe	Intervention	19	2
	Controls	14	4
Golomoti/ Mtakataka	Intervention	14	2.5
	Controls	0	0
Kandeu	Intervention	37	0
	Controls	29	0
Nsipe	Intervention	26	3
	Controls	47	0.5

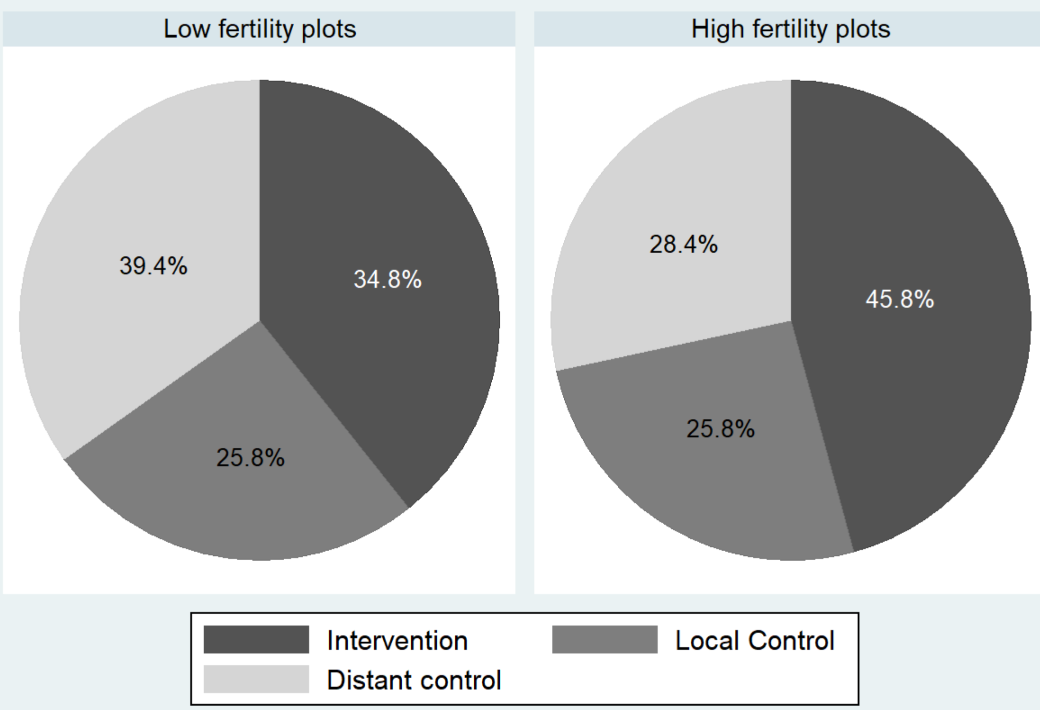
Notes: Nitrogen transport costs calculated from commercial fertilizer purchases due to data limitations. Zero values in maize transport costs are due to all sales within a cluster occurring at the field.

Figure 3A.1: Percent of high and low fertility plots in each EPA



Note: n=155 for each fertility classification

Figure 3A.2: Percent of high and low fertility plots in each sample group



Note: n=155 for each fertility classification

Table 3A.6: Percent of households on which total C on farmer-identified low fertility plot exceeded that on the high fertility plot ("misclassified") by EPA

	% of HHs that "misclassified" plots	% of HHs in EPA
Linthipe	9.5%	16.7%
	(n=4)	(n=24)
Golomoti	9.5%	21.1%
	(n=4)	(n=19)
Kandeu	28.6%	50.0%
	(n=12)	(n=12)
Nsipe	40.5%	37.8%
	(n=17)	(n=45)
Mtakataka	11.9%	45.5%
	(n=5)	(n=11)
All EPAs	100%	34.2%
	(n=42)	(n=123)

Note: Sample restricted to households for which total C values available for both farmer-identified plots.

Table 3A.7: Percent of households on which total C on farmer-identified low fertility plot exceeded that on the high fertility plot ("misclassified") by sample group

	% of HHs that "misclassified" plots	% of HHs in EPA
Intervention HHs	33.3%	28.6%
	(n=14)	(n=14)
Local Controls	26.2%	38.4%
	(n=11)	(n=11)
Distant Controls	40.5%	40.5%
	(n=17)	(n=42)
All EPAs	100%	34.2%
	(n=42)	(n=123)

Note: Sample restricted to households for which total C values available for both farmer-identified plots.

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