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VANISHING RETURNS?

POTENTIAL RETURNS AND CONSTRAINTS TO INPUT ADOPTION AMONG SMALLHOLDER FARMERS IN UGANDA

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ABSTRACT

This paper estimates the profitability of fertilizer and hybrid seeds in Uganda, using agronomic evidence on the yield returns to inputs from experimental fields, as well as output price data from local markets between 2000 and 2012. The results suggest that the returns to fertilizer are positive across the entire price range for beans, maize, and matooke and positive for the top 75 percent of prices for coffee. Commonly available improved seed varieties for maize and beans increase gains by 32 percent on average. However, accounting for the quality of the inputs available to farmers in the market, the sizable positive returns become negative for most of the price distribution, possibly explaining the low adoption of inputs in Uganda. The paper also examines the impact of other factors that could affect input adoption, by using a relatively long panel data set spanning 12 years. The analysis finds evidence that enhanced access to economic markets and past weather conditions have small effects on input use, and positive correlations between the use of extension services and knowledge and input use.

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Vanishing Returns?
Potential Returns and Constraints to Input Adoption among Smallholder Farmers in Uganda

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1. Introduction

Recently, Uganda has made impressive progress in terms of reducing poverty. The poverty headcount rate under the national poverty line declined from 31.1 in 2005/06 percent to 19.7 2012/13.[2] The majority of this poverty reduction can be attributed to the high growth in household agricultural income, at approximately 6 percent per year (World Bank, 2016). Key policies advanced by the government, mainly the stabilization of the conflict in the Northern region and infrastructure investments, contributed to agricultural income growth. There was also a component of good fortune: favorable rainfall and positive trends in commodity prices. However, only a small proportion of growth in household agricultural income can be explained by changes in the nature of production or an increase in the adoption of better technology in agricultural production (Barrett et al. 2017, World Bank 2016). Only around 40 percent of agricultural households *have ever* used improved agricultural inputs and there has been little progress in adoption over the 2005/16 to 2012/13 period. The low use of improved inputs by farmers remains a constraint for agricultural productivity and, therefore, for sustained poverty reduction in Uganda.

The objective of this paper is twofold: to explore the financial returns of using agricultural inputs and to examine what factors are constraining input use among Ugandan households. First, the returns to two key inputs -inorganic fertilizer and hybrid seeds- are examined to determine whether the inputs that are available to farmers in Uganda are profitable. The analysis explicitly examines net returns, not just increases in gross income. It takes into account the volatility of crop prices (Hill and Mejia-Mantilla 2017) and the problem farmers face in securing quality inputs (Bold et al. 2017). For the second objective, we test if some of the key constraints to input use identified in previous studies are present in the Ugandan context using a relatively long panel data set. This allows us to account for long-run household trends, while estimating marginal impacts that reflect a decade of changes. For this part of the analysis, we study the use of pesticide in addition to that of inorganic fertilizer and improved seeds.

Our results suggest that increased input use has the potential to drive productivity growth and render positive financial returns among smallholder farmers, despite the substantial output price volatility that characterizes Uganda. Yields of the four main crops considered[3]—maize, beans, matooke and coffee--increase in response to the application of inorganic fertilizer (nitrogen), particularly beans and maize. The gain is high across the range of output prices experienced from the year 2000 onwards. The economic return to fertilizer is always positive (across the entire price range) for beans, maize and matooke and positive for the top 75 percent of prices for coffee. Median returns are 180 percent, 74 percent, 64 percent and 39 percent respectively. Commonly available improved seed varieties for maize and beans increase gains by 32 percent on average. However, the cost of using maize hybrid seeds often exceeds the extra revenue gained from using them, reducing its financial return.

In addition, we find that the low quality of inputs prevalent in agricultural input markets, lower the financial returns, often to less than zero, which likely discourages input adoption. Thirty percent of herbicide samples contain less than 75 percent of the active ingredient (Ashour et al. 2016); hybrid maize seeds are equivalent to a mix of 50 percent hybrid and 50 percent traditional; and the average nitrogen

[2] Official poverty numbers estimated by the Uganda Bureau of Statistics (UBOS), using the Uganda National Household Survey (UNHS) 2005/06-2012/13.

[3] Under reasonable weather conditions, that is neither bad or particularly bad rainfall conditions.

content of fertilizer is 30 percent lower than it should be (Bold et al. 2017). The sub-standard quality of inputs that are typically available for farmers reduces the yield gain from using hybrid seeds and nitrogen to 75-87 percent of what is expected. As a result, the sizable positive returns to using nitrogen fertilizer and hybrid seeds for maize disappear and even become negative at many prices. The rate of return on fertilizer is only positive when maize prices are in the top two-thirds of the distribution.

In terms of the factors that affect input use, we find evidence that enhanced access to economic markets, and (good) past weather conditions marginally incentivizes input use among small farmers in Uganda. Access to markets positively affects the decision to use inorganic fertilizer and hybrid seeds but the effects are small: a 10 percent increase in the access to market index increases the probability of using inorganic fertilizer by about 0.01 percent. Similarly, weather conditions of the previous cropping season seem to matter slightly at the moment of deciding whether or not to adopt improved input for farmers in Uganda. A 10 percent increase in the water requirement satisfaction index (WRSI) positively affects the adoption of inorganic fertilizer, pesticide and improved seeds, by a 0.1 percent in the first case and 0.4 percent in the latter two. It is not clear whether this is a result of increased incomes or a result of altered expectations about future returns.

The availability of extension services and knowledge exhibits positive correlations with the adoption of improved inputs. The use of (any) extension services in the household's community increases the probability of improved seed use by about 6 percentage points, and of pesticide use by slightly less (5 percentage points), underlining the importance of social networks in the propagation of knowledge. However, it is not associated with the use of fertilizer, signaling that the content of the services provided could be more effective in promoting this particular input, given its potential returns. The adoption of all inputs considered in this study (inorganic fertilizer, pesticide and hybrid seeds) is highly correlated with households having participated in a National Agricultural Advisory Services (NAADS) training in the last 12 months – despite the fact that the correlation is smaller for fertilizer use. While it is not possible to establish causality, the results suggest that these extension services are important for smallholder farmers in Uganda.

Our main contribution is in estimating the hypothetical returns to input use for farmers, from a best-case scenario assuming high quality inputs and high output prices, to a scenario using lower quality inputs and low output prices. While the majority of studies regarding input adoption in the developing country context focus on programs or interventions that encourage adoption, only a handful of studies have focused on the actual quality of inputs. And only one study, to our knowledge, has directly tested different qualities of inputs in agricultural trials (Bold et al. 2017).

The paper proceeds as follows. Section 2 describes the trends and spatial patterns of input use in Uganda. Section 3 describes returns to input use examining the degree to which returns are present for the inputs available on the market in Uganda given input and output prices. Section 4 uses panel data to examine what factors are associated with the adoption of profitable inputs, while the last section concludes and offers policy recommendations.

2. Trends and spatial patterns of input use

The analysis in this paper uses data from about 3,000 households across Uganda, interviewed in the nationally representative Uganda National Panel Survey (UNPS) from 2005/6 to 2013/14. The Living Standards Measurement Study (LSMS) and Integrated Surveys on Agriculture (ISA) is a household survey program that supports the design and implementation of surveys such as the Uganda National Panel Survey (UNPS), and ensures comparability with other surveys being carried out under the LSMS-ISA project in Sub-Saharan Africa.

The UNPS has data on household characteristics, household consumption and income from a variety of income sources. It also contains a rich agricultural module. Five rounds of the UNPS are used in this analysis comprising data collected in 2005/6, 2009/10, 2010/11, 2011/12 and 2013/14. Households can be matched across rounds using a unique household identifier. The attrition in the UNPS was quite substantial between 2005/6 and 2009/10, but was moderate in the following two rounds (see Table 2.1). For the 2013/14 wave, the panel was rotated, and the survey lost a substantial portion of its original 2005/06 sample. For summary statistics, we use the sample of households engaged in agriculture weighted with cross sectional household weights. For the analysis of input adoption, we consider all households engaged in agriculture that were present in all five rounds of the UNPS: 1,108 households in total.

Table 2.1. Attrition in the UNPS by wave

	Sample	Original sample retention	Split-off HHs	Total
2005/06	3,123	100	0	3,123
2009/10	2,607	83.5	367	2,974
2010/11	2,564	82.1	305	2,869
2011/12	2,356	75.4	479	2,835
2013/14	1,320	42.2	1,799	3,119

Source: Uganda Bureau of Statistics (2013)

Maize, beans, matooke and cassava are the four most important crops as a share of total crop income for Ugandan smallholder farmers. Table 2.2 provides a description of the type of crops grown by the households for two of the latter years of the analysis. Maize and beans are universally important—comprising 10 percent or more of crop incomes in all regions in both years. Matooke is important in all regions except the Northern region, and cassava is important in all regions except the Western region.

For the most part, crops produced for household, domestic and regional consumption dominate crop income. Coffee is important for some households, and has been traditionally important for Uganda. Sunflower produced for commercial production has increased in importance in recent years, particularly in the north, but it is still a relatively small share of crop income and is also not considered further. Even though food crops dominate crop income, crop sales are important and increasingly so. The share of household income coming from crop sales has increased considerably, particularly for the bottom 40 percent: from 60 percent in 2005/06 to 72 percent in 2011/12 (Figure 2.1).

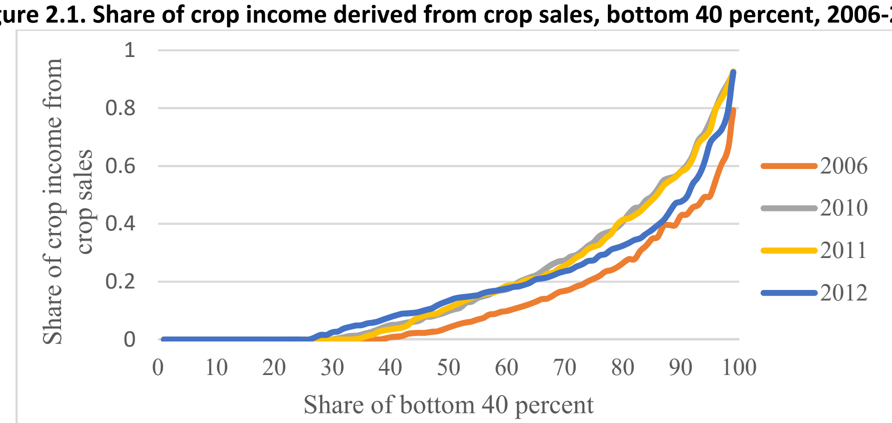
Interestingly, there has been little increase (or change) in the use of improved agricultural inputs. Figure 2.2.1 details the national trends in input use over time for households engaged in agriculture.[4] While the observed fertilizer use rate in 2013/14 (at 6 percent) was slightly higher than that observed for previous years, it has stayed constant at about 5 percent throughout 2005/06-2013/14. Pesticide use has been higher than that of fertilizer use, but the increase in use recorded in 2009/10 and 2010/11 disappeared, and only 15 percent of households were applying pesticides in 2013/14. In contrast, the proportion of households purchasing improved seed has been much higher, ranging between 17 and 24 percent. Improved seeds/planting materials are used for certain crops such as maize and cassava, and to a lesser extent beans and matooke (Figure 2.2.2). In Section 4 we investigate the potential factors behind these adoption rates.

Table 2.2. Share of crop income coming from each crop for selected waves

	2010/11					2011/12				
	National	Central	Eastern	Northern	Western	National	Central	Eastern	Northern	Western
Beans	0.17	0.16	0.10	0.16	0.25	0.16	0.18	0.11	0.13	0.21
Maize	0.12	0.12	0.17	0.12	0.07	0.17	0.15	0.25	0.16	0.10
Matooke	0.16	0.24	0.11	0.02	0.30	0.16	0.25	0.08	0.02	0.34
Cassava	0.11	0.12	0.16	0.13	0.03	0.11	0.09	0.15	0.14	0.04
Sweet Potatoes	0.10	0.12	0.10	0.09	0.07	0.09	0.15	0.11	0.06	0.06
Groundnuts	0.07	0.04	0.10	0.07	0.07	0.06	0.02	0.08	0.06	0.05
Coffee All	0.05	0.08	0.06	0.01	0.05	0.04	0.08	0.03	0.01	0.05
Sorghum	0.04	0.00	0.04	0.09	0.02	0.04	0.00	0.03	0.09	0.02
Finger Millet	0.03	0.01	0.05	0.03	0.02	0.03	0.01	0.06	0.04	0.02
Simsim	0.03	0.00	0.01	0.08	0.00	0.02	0.00	0.01	0.06	0.00
Sunflower	0.01	0.00	0.00	0.04	0.00	0.02	0.00	0.00	0.05	0.00

Source: Staff calculations using RIGA 2010/11-2011/12. Note: red indicates a share 10 percent and higher in a given region, green indicates a share between 3 and 10 percent in a given region.

Figure 2.1. Share of crop income derived from crop sales, bottom 40 percent, 2006-2012

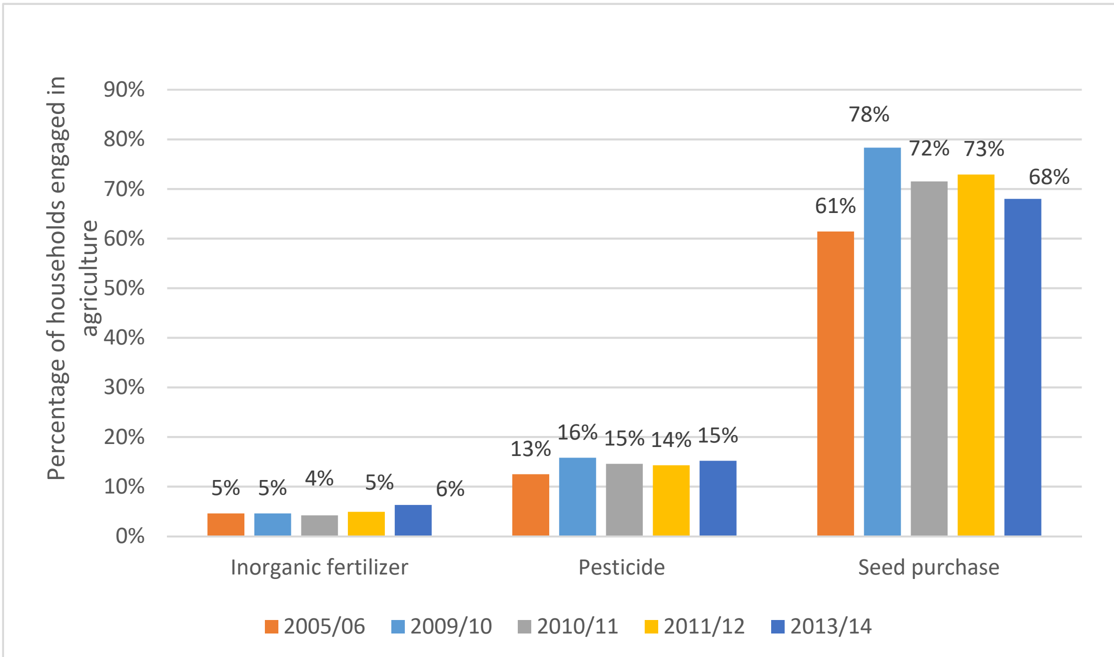


Source: Staff calculations using RIGA income aggregates calculated from UNPS 2005/06-2011/12.

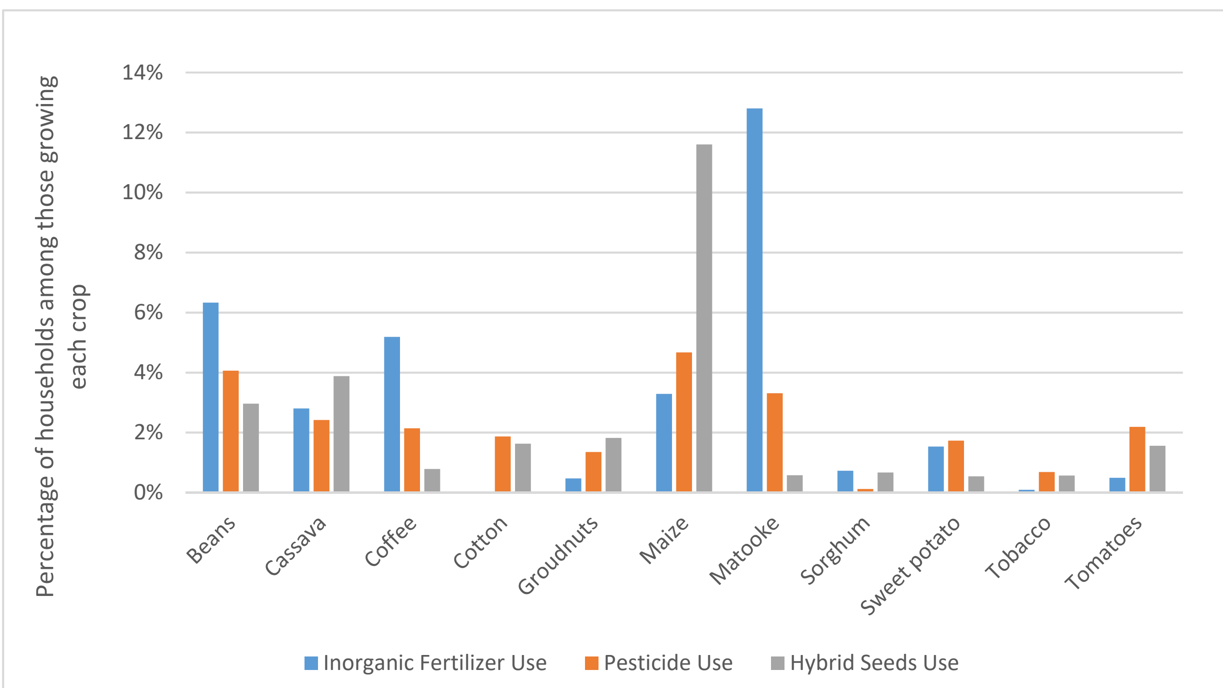
[4] The percent of households engaged in agriculture ranged between 75 and 82 percent throughout the 2005/06 - 2013/14 period.

Figure 2.2: Share of farmers using improved inputs, 2005/06-2013/14

1. Input Use, 2005/06-2013/14



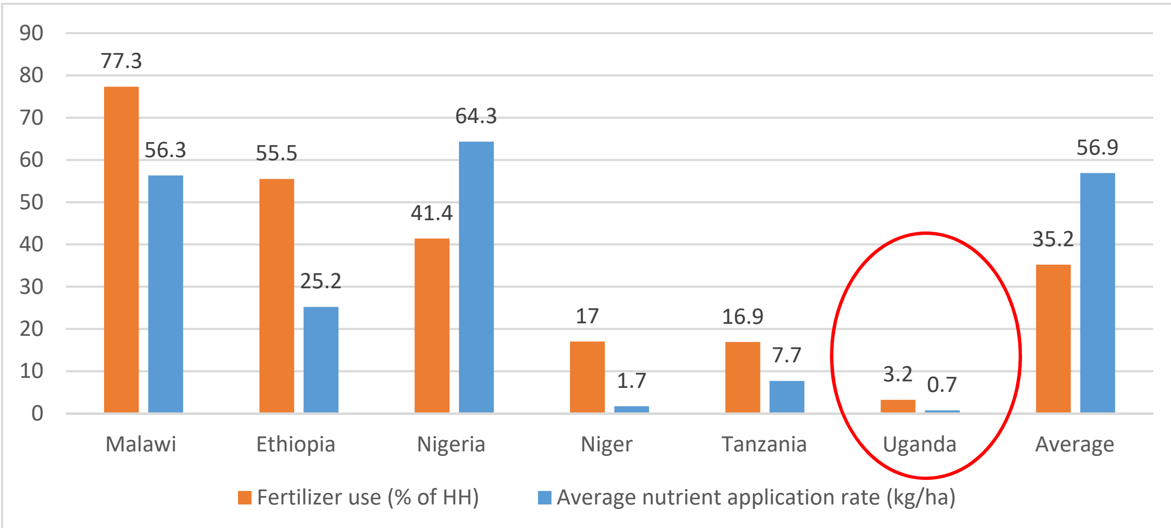
2. Input use by crop, average 2005/06 - 2013/14



Source: Staff calculations using UNPS 2005/06-2013/14.

Input use is low in Uganda compared to all other African countries for which comparable LSMS-ISA data are available. Previous studies such as Sheehan and Barrett (2017), and Binswanger and Savastano (2014) have analyzed the UNPS. Sheehan and Barrett (2017) provide a broad overview of input use in six Sub-Saharan African countries using the 2010 wave of the UNPS. Their work highlights the relatively low input use in Uganda compared to Ethiopia, Malawi, Niger, Nigeria, and Tanzania, and that the average amount of inorganic fertilizer applied per hectare of 0.7 kilograms for Uganda is substantially lower than the cross-country average of 56 kilograms per hectare (see Figure 2.3).

Figure 2.3. Use of inorganic fertilizer and application rates, 2010



Source: Sheehan and Barrett (2014), using comparable LSMS-ISA data.

The potential gains to input use appear quite high in Uganda given cultivatable land and output prices compared to other LSMS-ISA countries. Binswanger and Savastano (2014) develop a measure of agro-ecological potential (AEP) using international crop prices, the share of land under each crop, and the potential of the crop in that area from the 2005/06 and 2009/10 LSMS-ISA waves. The AEP is based on attainable crop yields across all agricultural zones using data from the International Institute for Systems Analysis and the Food and Agriculture Organization for medium input levels (Tóth et al., 2012). Uganda has the *highest AEP* (and the 4th highest AEP per capita) compared to all other countries at $1,878 per hectare, twice as high as the second runner up, Malawi, at $999 per hectare. However, these calculations assume the use of improved varieties, adequate fallows, and some mechanization, fertilizer application, chemical pest, disease and weed control. Smallholder farmers, who may be stuck in poverty traps, comprise more than 50% of Uganda's farmers and are precisely the individuals who may not be purchasing inputs, and who face variable input quality - a key element in explaining the lack of returns to input use. Similarly, McCarthur and McCord (2017) also predict high potential returns to input use, but also under the assumption that inputs are of high quality.

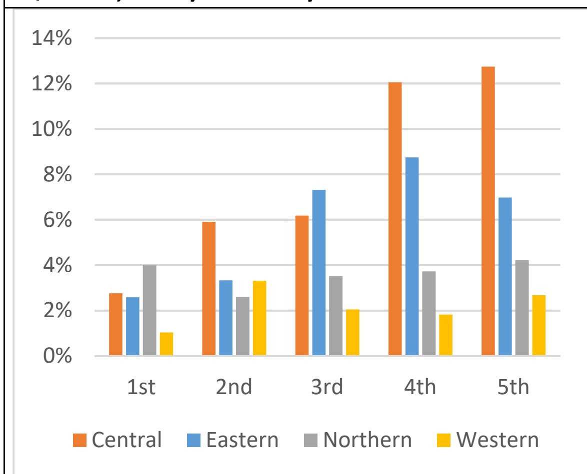
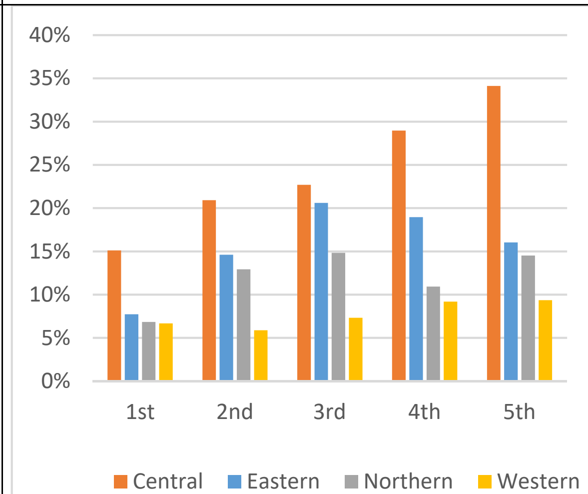
As in Suri (2011), the differences in input use are large across consumption quintiles and regions, depending on the predominant crops grown in the region.[5] Overall, poorer households have lower input

[5] The consumption aggregate used here is the aggregate constructed by the Uganda Bureau of Statistics, which uses the same method to generate the consumption aggregate used in their official poverty measures. The majority of the income aggregates come from the Rural Income Generating Activities (RIGA) database, which uses standardized

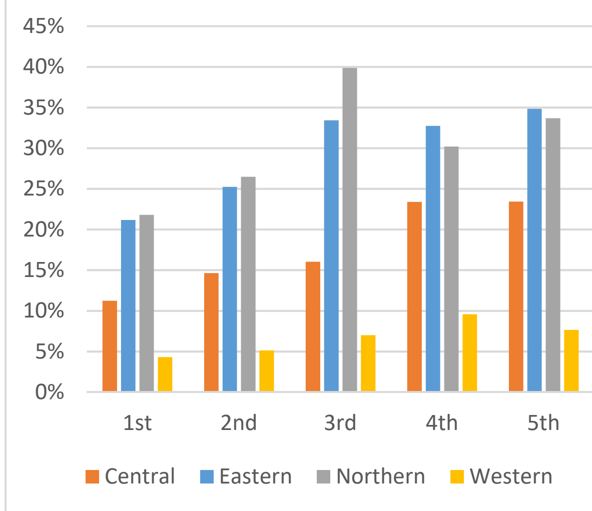
use rates across the different inputs, particularly when considering fertilizer and pesticide (Figure 2.4). The Western region lags in the use of all agricultural inputs. Also, the use rate of improved (hybrid) seeds in Uganda is considerably high compared to the rest of the agricultural inputs.

Moreover, the joint adoption of both inorganic fertilizer and improved seeds remains very low at an average of 3 percent over the period of interest, which limits the potential yield gain and could be harmful in the long run. These trends are consistent with the findings of earlier studies that show how the adoption of these complementary inputs is incomplete in Uganda (Nkonya et al. 2005 and Sserunkuuma 2005). Farmers tend to adopt improved crop varieties (hybrid seeds) without simultaneously applying fertilizer. This worsens soil fertility and yields in the long run, and can undermine the potential yield gain over time.

Figure 2.4: Poorer households in poorer regions are less likely to use inputs

<table>
<tr><td>1. Inorganic Fertilizer Use by Consumption Quintile, 2005/06 -2013/14</td><td>2. Pesticide Use by Consumption Quintile, 2005/06 – 2013/14</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td>3. Improved Seed Use by Consumption Quintile, 2005/06 – 2013/14</td><td></td></tr>
</table>

protocols to generate gross income aggregates across waves. Where inconsistencies were noticed they were communicated to the RIGA team and corrected in the protocols we used. The RIGA aggregates calculate crop and livestock income using information on the amount of goods produced by the household in the last 12 months and the price of these goods reported by the household. Prices are imputed from other sampled households when they are not collected. The measures of crop and livestock income calculated are gross income not netting out costs of land, labor or purchased inputs. Wage income is generated from data collected on wages earned in the last 12 months. The self-employment income aggregate calculated all self-employment income earned in the last 12 months and nets out the cost of purchased inputs. Purchased inputs can be quite a large share of the income from self-employment activities such as petty trading or handicrafts and netting out the cost of these inputs is important. For more details on how these aggregates are constructed, see Carletto et al. (2007).



Source: Staff calculations using UNPS 2005/06-2013/14

3. Returns to input use

In this section we examine the profitability from using improved inputs, taking into account the variability of the output prices and the quality of available inputs to farmers. We focus on the use of inorganic fertilizer and improved seeds for several of the main crops in Uganda described in Table 2.2: maize, beans, coffee and matooke.[6] We first estimate the inputs' profitability under optimal conditions using the best available information: agronomic evidence on the yield return to inputs from experimental fields, as well as output price data from local markets. We also briefly touch on the effects of sub-optimal weather conditions on these financial returns. We then study the potential returns under optimal conditions. Together with yield responsiveness and the historical distribution of agricultural output prices, we estimate whether the expected return to using modern inputs is, on average, positive for farmers in Uganda. Lastly, we consider the issue of the quality of inputs (for maize) and adjust returns closer to what an average farmer might actually obtain. More than 90 percent of households engaged in agriculture report buying their inputs from markets, shops and local vendors, according to the 2015 National Service Delivery Survey,[7] whose inputs rarely retain the same quality as those used in agronomic field trials.

3.1. Yield gains from the use of authentic inputs

It is often noted that experimental yields from controlled agronomic studies are high but rarely observed on an average farmer's plot. This can be explained by differences in soil and environmental conditions across farmers (Suri 2011, Harou et al. 2017), variation in crop management practices (Esilaba et al. 2005, Ngome et al. 2011, and Sileshi et al. 2010), and variation in access to high quality inputs (Tjernstrom et al. 2017, Fairbarn et al. 2017, Ashour et al. 2017, Bold et al. 2017). In this section we first consider yield returns observed in experimental studies to be able to provide an upper-bound estimate on the financial

[6] We did not find experimental field trials for pesticide use in Uganda or similar countries with detailed data on application rates and costs. Similarly, for coffee and matooke there was no evidence on improved seeds.
[7] The NSDS is collected by UBOS and contains information on the differences in services available for the Ugandan population, including agricultural services.

returns that farmers could experience. It draws heavily on the analysis by Bold et al. (2017), which conducts a unique, robust analysis of the quality of inputs available to farmers in Uganda and their resulting yield gains. In Section 3.3 we project returns where input quality varies, and show that input use becomes considerably less profitable with lower input quality.

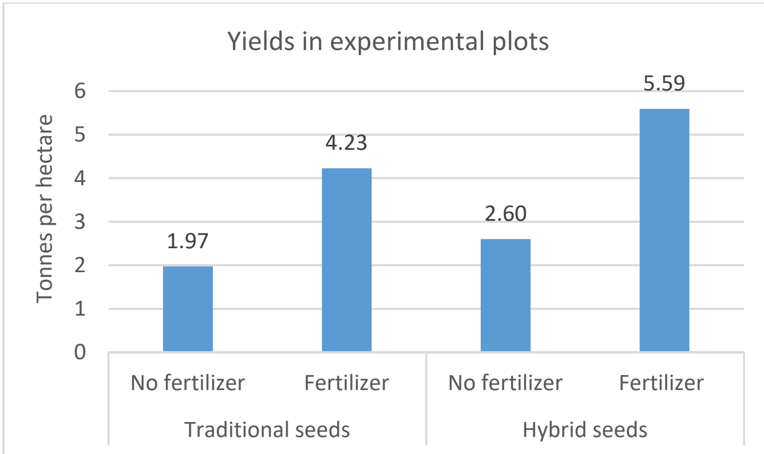
Maize yields increase substantially in response to the use of nitrogen fertilizer and when locally available hybrid seeds are used. Bold et al. (2017) present detailed estimates of maize yields under agronomic research conditions in Uganda for the following four scenarios: traditional seeds and no fertilizer, hybrid seeds and no fertilizer, traditional seeds and optimal fertilizer application—taken to be 108 kg of nitrogen per hectare—and hybrid seeds and optimal fertilizer application.[8] They show significant increases in yields from input use; yields more than double when fertilizer is used, regardless of the type of seeds used (hybrid or traditional). Yield gains are highest when both fertilizer and hybrid seeds are used, underscoring the complementarity of input use (Figure 3.1).

More broadly, yields of all crops increase in response to the application of nitrogen with the yields of rice, beans and maize being particularly responsive. Kaizzi et al. (2012a, 2012b, 2012c) document the returns to the use of nitrogen (N), Phosphate (P) and Potash (K) for a number of crops in Uganda. In general, across all crops, nitrogen application provides a significant yield gain, reflecting the fact that this is a main nutritional deficiency limiting crop growth. Rice, beans and maize are the crops that show the largest return to the use of nitrogen in their study. The yield gain from using nitrogen is shown in Figure 3.2. At the maximum, the additional yield from using nitrogen for maize is approximately 1.9 tonnes per hectare in Figure 3.2, which is of the same order of magnitude as the slightly larger gain recorded in Bold et al. (2017) and shown in Figure 3.1.

Rainfall anomalies reduce these yield gains. Thus far, good weather conditions are assumed. However, too little or too much rain reduces the yield gain from using fertilizer. This is documented in Christiaensen and Dercon (2009) for Ethiopia and is shown in Figure 3.3. The yield gain is largest, about a 33 percent increase, at median rainfall levels but is halved to about 15 percent when rainfall is too low (at the 25th percentile of the rainfall distribution) or too high (the top 25th percentile). Rosenzweig and Udry (2017) also report large variation in returns to investment in crop production in northern Ghana resulting from changing weather conditions. Ideal weather conditions (or at least non-extreme conditions) are assumed for the field trials used to determine the yield gains to nitrogen application. In the following section, we explore how the estimated results would be affected when weather conditions are not optimal using Christiaensen and Dercon (2009) as a reference.

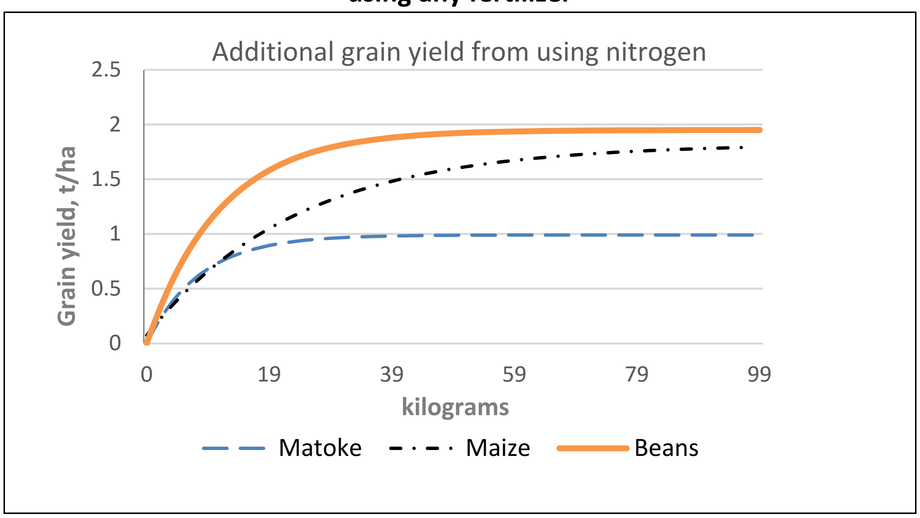
[8] Seeding in Bold et al. (2017) is done at a rate of 50kg per hectare and 108kg of fertilizer is applied per hectare in two applications.

Figure 3.1. Maize yields increase substantially when hybrid seeds are planted and nitrogen is used



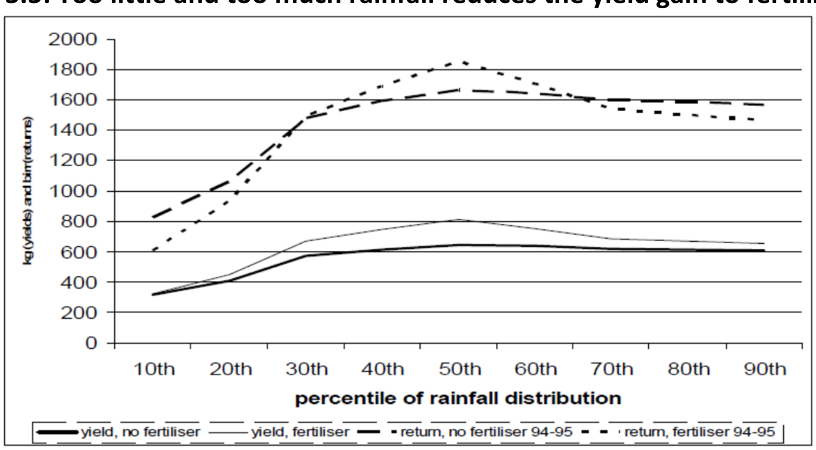
Source: Bold et al. (2017), returns to authentic inputs in experimental plots across 5 research stations in Uganda

Figure 3.2. Many crops show large yield increases in response to nitrogen application compared to not using any fertilizer



Source: Staff calculations using OFRA (2017) response functions for Uganda

Figure 3.3: Too little and too much rainfall reduces the yield gain to fertilizer use



Source: Christiaensen and Dercon (2011)

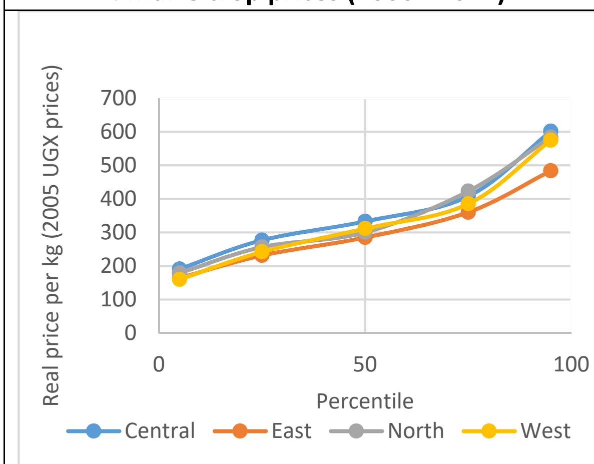
3.2. The net financial return to the use of authentic inputs

The ratio of crop output and input prices ultimately determines whether yield gains translate into increased profits for farmers. We now turn to examine the variation in relative prices across time to assess the profitability of input use for the average farmer.[9] We examine the agricultural inputs for which we were able to identify yields from controlled experimental studies undertaken in Uganda (mainly fertilizer and improved seeds) for crops that capture a high share of agricultural income in Uganda: maize, beans, matooke and coffee (see Table 2.2).

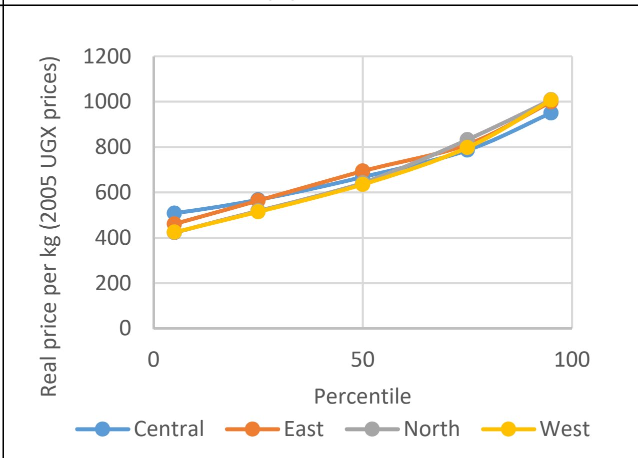
Although input prices are stable over time, crop prices are volatile. There has been some, but relatively modest, variation in the cost of inputs in Uganda over the period 2005/06-2013/14, as shown in Figure 3.4.4.[10] However, there has been considerable variation in crop prices. This is particularly relevant for the adoption of inputs, as fluctuations in wholesale prices are often passed on to producers who then receive a smaller market share, particularly at the farm-gate when they sell their crops (Fafchamps and Hill 2008). Figure 3.4 details the volatility in the real wholesale price of maize and matooke from 2000 to 2012 using data on wholesale prices collected by the Uganda Bureau of Statistics (UBOS) in 8 markets as part of price data collection for the consumer price index (CPI). The graphs show the distribution of prices using data only from months in which farmers typically sell (namely November to February and June to August, as reported in the UNPS survey). The price distribution is analyzed separately for each of the four regions.

Figure 3.4. Distribution of real crop prices

1. Maize crop prices (2000 - 2012)



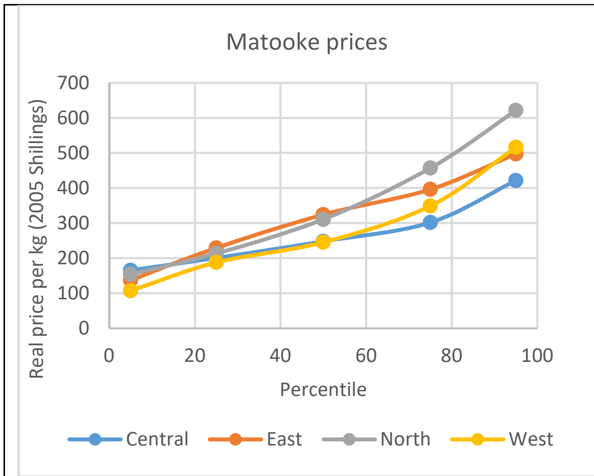
2. Bean crop prices (2000 - 2012)

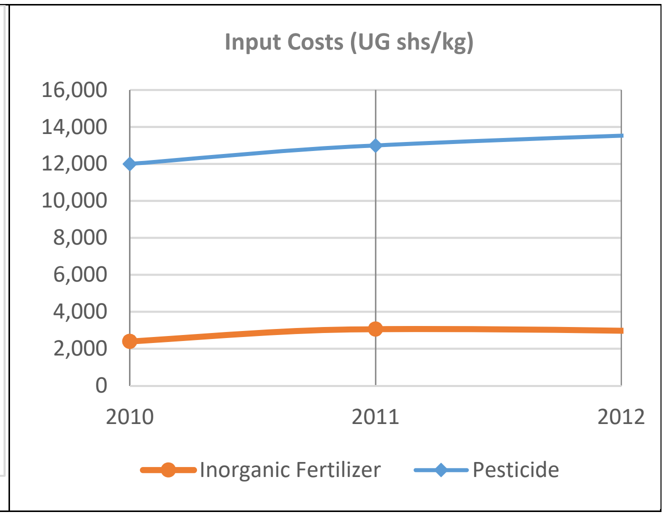


3. Matooke crop prices (2000 - 2012)

4. Input prices (fertilizer and pesticide, UG shs per kg.)

[9] As mentioned, prices are likely to be related to how easily farmers can access input and output price markets. In Section 4 we examine the role of distance to markets in influencing input adoption for farmers.
[10] We only include fertilizer and pesticide, because there was no information on the quantity of hybrid seeds used.





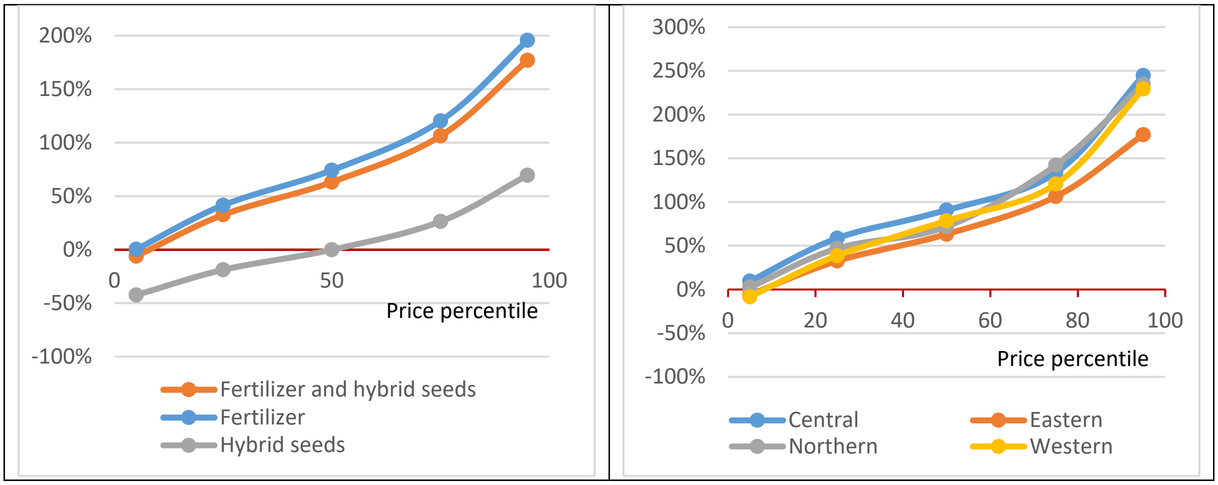
Source: Staff calculations using wholesale prices from UBOS, 2000 - 2012 and UNPS 2005/06-2013/14. Prices are averaged across the 1st and 2nd season.

Using the range of output prices shown in Figure 3.4, we first calculate the return to applying nitrogen (inorganic fertilizer) for the main maize growing region, the Eastern region. Figure 3.5.1 plots the distribution of the net financial return per hectare to using maize hybrid seeds and applying nitrogen to maize across the range of prices. It uses the average yield return estimated in Figure 3.1 assuming reasonable rainfall conditions, and the average cost of inputs in 2013, as specified in Bold et al. (2017). The estimates show that when crop prices are at their lowest, returns to fertilizer use are almost 0 (bottom 5 percent of prices) and at median prices returns are 74 percent. At the highest crop prices (top 5 percent of prices), returns are a substantial 196 percent.

While the use of hybrid seeds enhances crop yields, their cost often exceeds the extra revenue gained from using them. As a result, the rate of return to using hybrid seeds alone is negative except when output prices are very high. The returns are positive for the top 50 percent of maize prices, but at median prices the rate of return to using hybrid seeds is zero. As a result, yield gains are highest when using hybrid seeds and nitrogen together; the return to their joint use is lower than the rate of return to using fertilizer alone. The rate of return is negative until the 20th percentile of the price distribution, and is 34 percent at median prices. Figure 3.5.2 plots the return to using a package of fertilizer and seeds in different regions. Returns are similar for farmers in all regions, but lowest in the Eastern region.

Figure 3.5. The returns to nitrogen use are high across a range of prices, but not so for hybrid seeds.

1. Rate of return to fertilizer and hybrid seeds for Maize in the Eastern Region	**2. Rate of return to fertilizer and hybrid seeds for Maize across regions**



Source: Staff calculations using yield responsiveness and cost of inputs estimated in Bold et al. (2017) and wholesale prices from UBOS, 2000 - 2012.

Next, we compare the returns from applying fertilizer and improved seed for four major regional crops in Uganda (UBOS 2009): maize in Eastern Uganda, beans and coffee in Western Uganda, and matooke in Central Uganda (Figure 3.6). As above, our returns vary with the distribution of output prices, while input costs remain fixed. See the Appendix for the method and values used in each of these calculations, including prices, fertilizer application rates, and yield responses. It is worth noting that we are not considering the effects of long-term soil quality; the continuous use of improved seeds requires more nutrients and their use degrades soil quality in the long run. Thus, the non-diminishing returns to improved seed use over the long-term depend on the fertilizer use term; and therefore, we expect the returns to improved seed to be overstated, particularly if fertilizer use is as low as it is in Uganda.

We observe that returns to fertilizer are present across all crops, and high for a range of prices. For beans and maize, the median returns are 74 percent and 66 percent respectively. There are positive returns for both fertilizer and improved seeds across the entire range of prices, but the returns to investing in hybrid seeds and fertilizer together are no higher than investing in just fertilizer alone.[11] For matooke and coffee, tree-based crops, median returns are 66 and 39 percent, respectively. Positive returns are present at all prices for matooke and for the top 75 percent of prices for coffee.[12] Robusta coffee requires the highest application rate of fertilizer (190 kg per hectare compared to 45 kg per hectare for matooke). Thus, at these rates of return, we should expect high rates of fertilizer use.

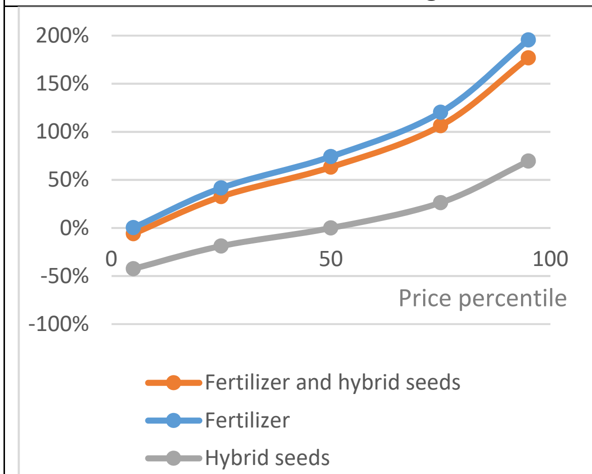
That said, the latter returns assume normal weather conditions, and under poorer weather conditions the financial returns likely disappear. If the yield gain is halved under bad weather conditions as some studies suggest (Christiaensen and Dercon 2011, Rosenzweig and Udry 2017), the financial returns become negative for all coffee prices and all but the top 25 percent of maize and matooke prices. In contrast, the return to fertilizer use on beans remains positive across the full range of prices (see Figure 3.7). The expected return for fertilizer use will depend on the full distribution of possible returns under all weather and price outcomes, which is not possible to estimate with the available data. However, if farmers are risk

[11] These returns are also specific to the particular seed used and region, the Western region. For beans we used the returns from K132 and Kanyebwa seeds from Kaizzi et al. (2012).
[12] Yield increases are taken from Nyombi et al. (2010) for matooke and van Asten et al. (2017) for coffee. In neither study were returns to improved planting materials for matooke or coffee, for example, considered.

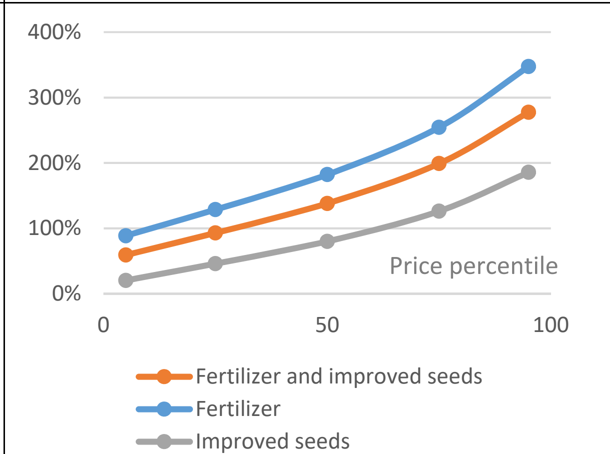
averse as studies suggest (Binswanger 1980, Brauw and Eozenou 2014), then a large expected return may be needed in order to offset the disutility from negative returns. Indeed, coffee farmers have been shown to reduce input use in Uganda as a result of expected risk in prices and weather (Hill 2008). In the presence of risk aversion and uncertain returns, returns to using fertilizer in maize and matooke production, even when assuming high quality inputs, may not be enough to encourage adoption.

Figure 3.6: Returns to authentic inputs across major crops

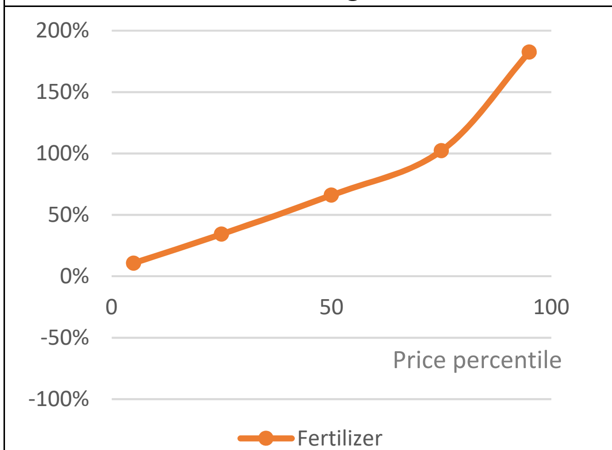
1. Returns to fertilizer and improved seeds for maize in the Eastern region



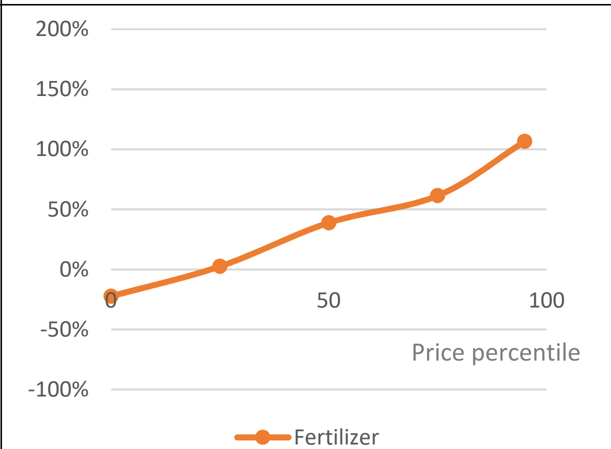
2. Returns to fertilizer and improved seeds for beans in the Western region



3. Returns to fertilizer for matooke in the Central region

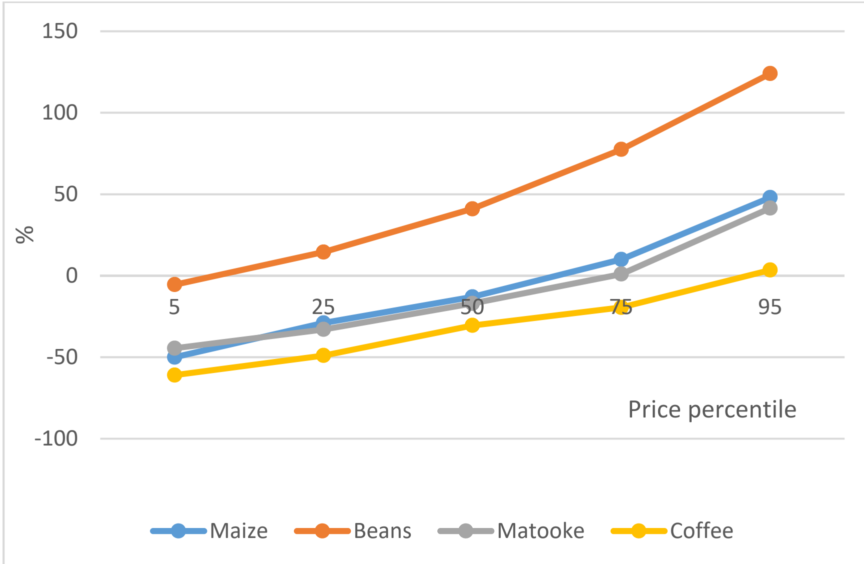


4. Returns to fertilizer for Robusta coffee in the Western region



Source: 1: see Figure 3.5, 2-4: staff calculations using yield responsiveness and cost of inputs estimated in the OFRA Response Function Database (2017) from the University of Nebraska. Wholesale prices from UBOS, 2000 - 2012.

Figure 3.7: Predicted returns to fertilizer use under bad weather conditions



Source: Staff calculations using yield responsiveness and cost of inputs estimated in the OFRA Response Function Database (2017) from the University of Nebraska and in Bold et al. (2017) and wholesale prices from UBOS, 2000 - 2012.

3.3. Quality of input use

The quality of inputs in markets frequented by farmers is commonly low in Uganda. A 2014 Deloitte study finds that low quality inputs in Uganda are most common in the maize herbicide market, followed by maize seeds and fertilizer. In the country, low quality has been associated with bulk breaking – that is, when smallholder farmers demand quantities of fertilizer or seed that are smaller than the contents of the package. For example, fertilizer is sold in 50 kg bags, but farmers will often demand fertilizer in 1 kg, 2kg or 5kg bags. Similarly, seed companies package seed in 2kg bags while farmers often demand smaller quantities than this. When selling these smaller quantities, the input can either be diluted and/or the label is counterfeited. This problem is particularly worrisome, as a large majority of farmers report buying their agricultural inputs from the market. According to the 2015 National Service Delivery Survey (NSDS), a little more than 90 percent of the households engaged in agriculture obtain their herbicides, fungicides, pesticides and fertilizer from the market, shops or local vendor. In the case of hybrid seeds, the share drops to 64 percent (see Figure 3.8.1).

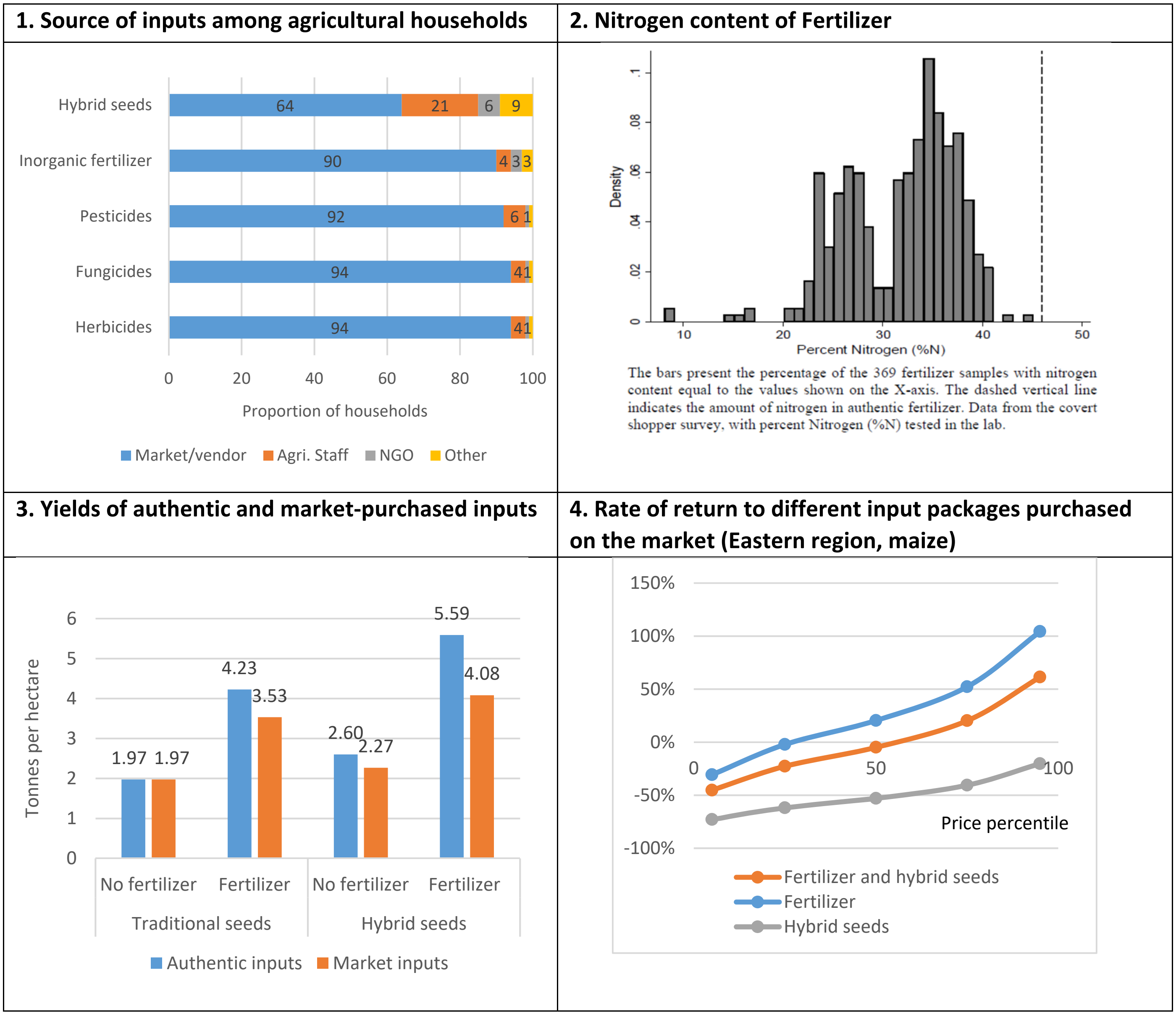
Recent economic studies have carefully quantified the magnitude of the counterfeiting problem in these markets. Ashour et al. (2017) collected data on 483 samples of herbicide across 120 markets in Uganda and find that 30 percent contain less than 75 percent of the active ingredient advertised. Similarly, in Bold et al. (2017), 369 samples of fertilizer purchased from 129 retail shops by a mystery shopper, *no samples* were found to contain the required nitrogen content. The average nitrogen content was 30 percent lower than what it should be (Figure 3.8.2); a larger shortfall than the 10 percent shortfall found in neighboring Tanzania (Fairbarn et al. 2017). The Bold et al. (2017) study also finds that the average quality of hybrid seeds purchased at 30 retail shops was also below standard, and estimated to be equivalent to a mix of 50 percent hybrid seeds purchased directly from the seed dealer and 50 percent traditional seeds purchased from farmers.

These sub-standard qualities of inputs that are typically found in markets reduce the yield gain from using hybrid seeds and fertilizer for maize to 75-87 percent of what is expected. Figure 3.8.2 compares the yield gain from using authentic inputs for maize with the yield gain from using the average quality of inputs typically purchased, i.e. fertilizer with 30 percent less nitrogen and hybrid seeds mixed with equal parts of traditional seeds. Yields using sub-optimal fertilizer are reduced to 75-83 percent of what is expected, and yields using sub-optimal improved seeds are reduced to 87 percent of expected yields (Bold et al. 2017).

As a result, the sizable positive returns to using fertilizer and hybrid seeds for maize disappear and even become negative at many prices. The rate of return to fertilizer at median prices in Eastern Uganda falls from 74 percent, when authentic fertilizer is used, to 20 percent, when fertilizer purchased on the market is used (Figure 3.8.4). Thus, the rate of return on fertilizer is only positive when maize prices are in the top two-thirds of the distribution. Similarly, positive rates of return for adopting both fertilizer and hybrid seeds are only observed when prices are in the top half of the price distribution, when quality is taken into account. As for the returns to just using hybrid seeds, owing to yield loss, they are negative across the entire price distribution, suggesting that farmers should not adopt seeds bought in the market. Interestingly, in 2008, 53 percent of households reported that the main reason for not using agricultural inputs was lack of knowledge, and this figure dropped to 27 percent by 2015. In that year, the cost and the concern that inputs were not useful increased. Thus, if farmers' beliefs about the quality of inputs are accurate, which studies such as Gilligan et al. (2017) show, then farmers' uncertainty about quality can limit adoption.

There still may be positive returns to using fertilizer on beans after accounting for the quality of the fertilizer. Unfortunately, we do not have figures on the yield response for beans, coffee and matooke under inauthentic inputs; however, given that the range of the return for authentic inputs is in line with that of maize's returns to authentic inputs, we expect a similar downward shift in the distribution of returns should input quality be suboptimal. If this were the case, using fertilizer on coffee would likely never be optimal and using fertilizer on matooke would only be optimal at higher prices, as with maize.

Figure 3.8. The extent and impact of poor quality inputs (maize)



Source: Figure 1: 2015 NSDS. Figures 2 and 3: Bold et al. (2017). Figures 4 and 5: Staff calculations using yield responsiveness and cost of inputs estimated in Bold et al. (2017) and wholesale maize prices from UBOS, 2000 - 2012.

Securing high output prices is highly correlated with a farmer's ability to network and physically access markets. Thus far, we have considered the hypothetical range of returns to farmers. However, even if returns remain possible under high output prices, there may only be a select number of farmers who are adept at securing high output prices. For this reason, we should control for household characteristics in examining the decision to adopt inputs. In Section 4 we use the five-year UNPS panel data described in Section 2 to examine how factors such as distance to markets, lagged rainfall, extension services and loan access impact the decision to adopt inputs controlling for household fixed effects and plot characteristics.

4. Factors associated with the adoption of inputs

It is well established that sustained agricultural growth, paired by an increase in the productivity of the sector, is a necessary condition for a successful structural transformation and for the reduction of poverty. Augmented agricultural productivity is closely linked to the increase in the adoption of improved or modern agricultural inputs, as was the case of the Indian Green Revolution, and to a lesser extent, in countries of Latin America (McCarther and McCord 2017). While in other countries of Sub-Saharan Africa the use of fertilizer and other agro-chemicals is higher than often acknowledged, this is not the case in Uganda (Sheahan and Barrett, 2017).

In this section, we shed some light on other factors, besides financial returns, that influence agricultural input use by smallholder farmers in Uganda. We first briefly review the literature on agricultural input use, drawing lessons for the Uganda context. Then, we use the UNPS panel data set, described in Section 2 and spanning 8 years, to assess what factors are correlated with input use. More specifically, we look at the degree to which access to markets, weather conditions and prices affect input use, and also assess how usage rates correlate with extension services and certain household/farm characteristics.

4.1 What does the literature on adoption tell us about what constrains adoption?

The economics literature analyzing the constraints to agricultural technology adoption in a smallholder setting has evolved from studying a farmer's production function -primarily in the US- to understanding the limitations that farmers in less developed countries face.[13] Foster and Rosenzweig (2010) provide a comprehensive overview.[14]

Initially, studies on input adoption identified labor availability, price uncertainty and household preferences as main constraints to adoption. The first studies on technology adoption, developed within the agricultural economics literature, analyzed the production functions in the context of US agriculture. Farm size (Just and Zilberman 1983, Hennessy 1997), complementarities in adopting multiple technologies (Dorfman 1996), output price uncertainty and variability (Kim et al. 1992), and the substitution between on and off farm labor (Dorfman 1996, Diiro and Sam 2015) were the major predictors of adoption among

[13] Here technology refers to both agricultural techniques, such as soil and water management, and improved agricultural inputs: seeds, fertilizer, and pesticides.

[14] Other broad reviews include: Sunding and Zilberman (2010), who consider institutional as well as technological innovations in promoting adoption; Sanders and Shapiro and Ramaswamy (1996) provide an overview of technology development for improved agricultural growth in semi-arid Sub-Saharan Africa over the previous 3 decades, recommending adoption of intensive technologies in conjunction with water retention techniques and fertilizer application; Rogers (1995) provides an overview of network characteristics aiding diffusion, and Hall (2005) reviews the complementary skills and capital goods needed for adoption to stick; Mullaly et al (2013) review empirical randomized trials regarding technology adoption; Jack (2011) studies specific market inefficiencies (land, labor, credit, risk, input and output markets) preventing adoption and Maertens and Barrett (2012) provide an overview of social learning studies and technology adoption; and De Janvry et al (2016) provide an overview of field experiments studying technology adoption within each of these topics.

farmers. Several studies, both theoretical and empirical, investigate the role of attitudes towards risk (Tsur 1990, Koundouri et al. 2006), with some attempting to estimate farmers' risk preferences (Hellerstein et al. 2013) and to identify the degree to which risk and ambiguity affected take up given the lack of agricultural insurance (Barham et al. 2014).

Access to markets, together with population growth, has been linked to the process of intensification of agriculture, comprising of higher usage rates of modern inputs. Under the Boserup-Ruthenberg framework, population growth and market access leads to more intensive land use, which results in the need to adopt improved technologies such as fertilizer and hybrid seeds, irrigation and mechanization (Boserup 1965, Ruthenberg 1980, Binswanger and Savastano 2017). One can also think of a more direct effect of access to markets, in terms of the availability and affordability of agricultural inputs for farmers, explained by lower transportation and transaction costs.

The more recent introduction of randomized controlled trials (RCTs) has allowed studies to causally identify factors constraining input use and quantify their importance. De Janvry et al. (2016) provide an overview of the field experiments in developing countries on agriculture, emphasizing that the vast majority of RCTs have focused on "the adoption, diffusion, and impact of technological and institutional innovations in agriculture." This includes the impact of removing credit and liquidity constraints as well as the provision of insurance, the role of information in decision making, which includes extension training and learning via social networks. We cover each of these areas below, highlighting where RCTs were used to identify the constraints to technology adoption in agriculture.

A number of studies have examined imperfections in rural credit and insurance markets. Most find that binding credit constraints and limited insurance markets negatively affect adoption (Rosenzweig and Binswanger 1993, Croppenstedt et al. 2003, Gine and Klonner 2005, Dercon and Christiansen 2011). Dercon and Christiansen (2011) show that the combination of credit constraints, failing harvests, and lack of insurance contribute to farmers remaining in low-risk low-return agriculture practices in Ethiopia.

Lack of information about new technologies is also found to be a major constraint. Extension workers play an important role in spreading information regarding new technologies and techniques in agriculture. However, there are mixed findings on the effectiveness of extension agents. Anderson et al. (2007), Birkhaeuser, Evenson, and Feder (1991) and Evenson (2001) provide a review of the impact of access to extension training on production. Overall, there is considerable difficulty in scaling extension operations and their effectiveness often depends on changing policy environments. Further, extension agents' work is not always tractable, both in terms of whom they reach and what is taught and learned by farmers. For example, better farmers may be selected for training, or seek out extension agents for advice. For this reason, RCTs have been instrumental in helping tease out the effects of extension services.

Gilligan et al. (2009) provide one of the earlier causal studies quantifying the impact of extension training on poverty and consumption. They find that receiving at least one extension visit reduces the headcount poverty rate by 9.8 percentage points and increases consumption growth by 7.1 percent in Ethiopia. Kondylis et al. (2014) look more carefully at how a new technology diffuses using "training and visit" extension models in an RCT framework in Mozambique. They find that information diffuses more effectively if contact farmers within villages are directly trained in the same central location as extension agents, rather than extension agents training contact farmers, who then are expected to share the information with other villagers. Mobarak and Yishay (2017) test alternative methods to extension training in an RCT framework to promote pit planting and Chinese composting for maize in Malawi. They find that peer farmers (PF) are more effective at promoting adoption than using traditional extension when provided with monetary incentives.

Information communication technologies (ICTs) have also increasingly played a part in extension training and information dissemination. Campenhout et al. (2016) conduct a randomized controlled trial among 248 farmers in Uganda to estimate the effect of teaching potato farmers about seed practices via videos. They find that videos are an effective tool at increasing knowledge about the practices shown; test scores increased, in the order of 9 percent, for correct seed selection practices, and as much as 28 percent for correct seed storage practices. Cole and Fernando (2012) conduct an RCT in Gujarat, India testing the effects of a mobile phone based agricultural consulting service. They show that farmers increase their use of effective pesticides and riskier crops such as cumin. However, Fafchamps and Minten (2012) show that access to more factual information, such as prices and weather information does not affect outcomes, including crop varieties, prices received, or cultivation practices.

Related to extension training, a number of studies underscored the importance of social networks and social learning as a determinant of adoption, particularly for new technologies. Even if farmers have access to inputs, credit and extension training, the discovery process in agriculture is slow and risky– an entire season is necessary to test if a new technology is successful and cost effective. Without sufficient capital, or large enough farms to experiment on, risk averse farmers are better off observing the outcomes of early adopters. Krishnan and Patnam (2014) show that extension services can help facilitate learning, but that the impact is smaller than the impact of social learning. However, their study does not provide a causal estimate of social network's effects, and suffers from the well-known reflection effect (Manski 1993).[15] Studies such as Udry and Conley (2010) overcome this by acquiring high frequency data. They show that for new agricultural technologies farmers mimic the input choices of their successful neighbors, and update choices given their own experience with the crop each period. Bandiera and Rasul (2006) also study learning and establish their well-known inverted U-shaped adoption curve, namely that social effects on individual adoption are positive with few adopters in an individual's information network, and negative when there are many.

The latter studies, however, do not provide causal estimates of network effects. RCTs have helped overcome the inherent endogeneity of network effects. More recent studies have used RCTs to test the degree to which central actors in networks can be utilized as injection points for new information to be disseminated in a village network and their efficacy is compared to standard extension trainers (Mobarak and Yishay 2017, Kondylis et al. 2014). In a similar vein, Vasilaky and Leonard (2017) look at the impact of weak ties in the presence of agricultural information regarding a relatively new cash crop, cotton in Uganda. They pair farmers who do not know one another and encourage them to share information while learning about a new technology. This intervention proves to be as effective at increasing mean yields as a standard extension-training program. Overall, extension programs that harness social networks can better overcome the slow and risky process of learning, especially for new technologies.

Insights from behavioral economics have also highlighted the importance of behavioral constraints in limiting investments in inputs. At the times at which input purchases ought to be made, farmers can be at their poorest (Mani et al. 2013) and their bandwidth to take on new ideas at this point is limited. Similarly, present bias when disposable income is high can impact decision making, particularly with regards to

[15] The reflection effect refers to the idea that individuals' choices may be correlated with their peers' choices only because all their outcomes are driven by or "reflect" common unobservable shocks or trends.

future investments. Thus, Duflo et al. (2011) find that providing farmers with input price subsidies during harvest times can help overcome this problem. They show that providing time-limited subsidies to fertilizer just after harvest, when farmers have money, can result in sizeable changes in fertilizer use in Western Kenya. This implies that farmers may require market incentives to overcome behavioral limitations such as present bias.

Overall, the economic literature provides several key lessons in terms of what factors affect technology adoption among smallholder farmers. First, the technology should be easily available and of reasonable quality for the farmer to even try it. Low output price fluctuation and well-functioning credit and insurance markets are also factors that promote input adoption. Similarly, the availability of information, through extension services and training often results in increased adoption, particularly if paired with social networks. Social networks and ICTs can leverage the knowledge imparted by extension programs alone, and help to increase their impact. For technologies that have been in use, such as fertilizer and improved seeds, opportune subsidies for inputs that encourage purchases when farmers are least cash constrained can also jump-start adoption. With positive net returns, farmers are more likely to purchase the inputs in subsequent years.

4.2 What do we know about farmers who adopt inputs in Uganda?

In this section, we make use of five rounds of the Uganda National Panel Survey 2005/06-2013/14 to examine whether some of the relevant factors identified in the literature are associated with input use in Uganda. More specifically, we look at the degree to which access to markets, past weather conditions and prices affect input use. We also assess how usage rates correlate with information and training, credit access and certain plot characteristics. We are unable to consider the role of behavioral factors, due to a lack of good measure of these in the panel data survey. In addition to inorganic fertilizer and hybrid seeds (for which we analyzed the financial returns in Section 4), we consider the use of pesticide, also critical in increasing overall agricultural productivity.

First, improved access to economic markets should enable input use by farmers. Better access to economic markets should facilitate the availability of agricultural inputs for farmers, and should also be an incentive their use as it facilitates the commercialization of the final output by lowering transportation costs. Following a common approach in the literature (see Blankespoor et al. 2016), for every household in each year of the panel, we use a domestic market access index that is a function of the weighted sum of the population of cities with a population larger than 100,000 inhabitants, where the weight decreases with transport time.[16]

More specifically, the definition of market access in a household location *i* at time t ($MA_{i,t}$) is the following:

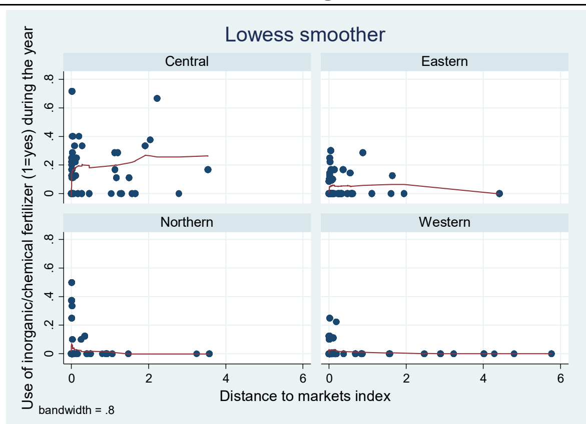
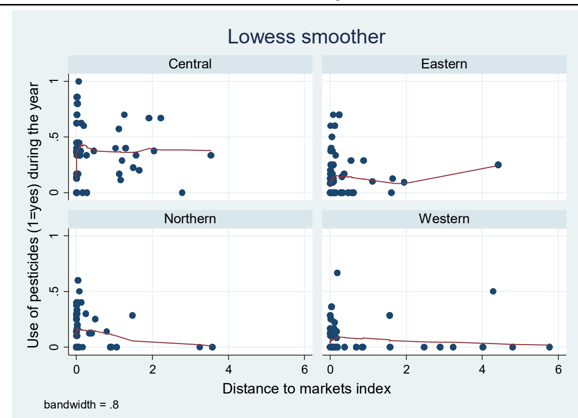
$$MA_{i,t} = 1 + \sum_{j \neq i} P_{j,t} \tau_{ij,t}^{-\theta}$$

[16] We thank Brian Blankespoor for the support in estimating the market access index.

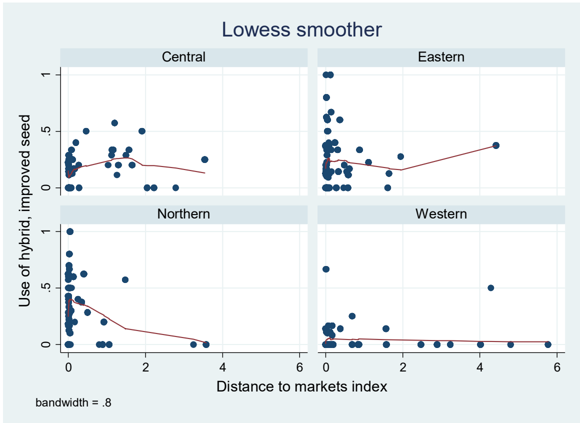
where $P_{j,t}$ is the population in city j at time t, $\tau_{ij,t}$ is the travel time between locations i and j at time t, and θ is a trade elasticity parameter.[17] The travel time varies over the years based on geo-referenced information on road categories, surface type and condition, information derived from the Uganda National Roads Authority (UNRA) (see the Appendix for a more detailed description). A higher value of the index indicates that households have better access to markets (where both agricultural inputs and outputs are sold) in terms of proximity to larger markets and/or shorter travel time to a given market. The variation arises both from the changes in the quantity and quality of the road network available to the household, and the demographic growth of the different markets close by.

Input use tends to increase with enhanced market access in Uganda, particularly in the Central and Western regions. Figure 4.1 examines how input use varies with access to markets. Given that market access and crop types vary across regions we present this for the four regions separately. With the exception of some outliers, farmers in villages with better access to markets have higher use rates of fertilizer and to a lesser extent, pesticide and hybrid seeds. This seems to be particularly true in the more economically integrated regions: the Central and Western regions.

Figure 4.1: Access to markets index and input use (at the village level), by region

1. Use of inorganic fertilizer	2. Use of pesticide
	
3. Use of hybrid seeds	

[17] Following Donaldson (forthcoming), the elasticity of trade, θ, is equal to 3.8. Different values of the trade elasticity parameter provide alternative results for robustness checks (e.g. see Jedwab and Storeygard 2015; and Blankespoor et al. 2016).



Source: Staff calculations using UNPS 2005/06-2013/14

Other factors that are likely to affect the decision to adopt agricultural inputs are weather conditions and agricultural prices.[18] Given that the decision to adopt agricultural inputs is taken early on in the cropping season, we analyze whether lagged values of weather index and agricultural output prices affect a farmer's decision to use inputs. Past weather conditions may affect the present decision to use inputs through short-term bias. Individuals tend to weigh recent information more heavily when making a decision, and thus, if the previous season was a good one (bad one) as a result of good weather conditions (bad weather conditions), it is likely that the farmer will decide to (not) use inputs. We measure weather conditions through the Water Requirement Satisfaction Index (WRSI), which is estimated based on a maize crop model using satellite rainfall data at the sub-county level.[19] The index ranges from 0 to 100, where 100 means there was no deficit in the water needed, and each household was assigned the average between the main and short seasons for the previous cropping season. As shown in Figure 4.2, weather conditions vary considerably across regions and over time.

Similarly, lagged output prices may affect input use as they are usually a good predictor of current prices, as evidenced by the fact that commodity prices (particularly maize and banana) are often characterized by autocorrelation models of order one (Deaton and Laroque 2003, Cafiero at al. 2005). Thus, if prices were high in the previous cropping season, the farmer may expect similar prices for the current season and decide in favor of adopting inputs. For the analysis, we use the same set of prices used to estimate the financial returns in Section 3: wholesale prices collected in eight different markets by UBOS for the construction of the CPI.

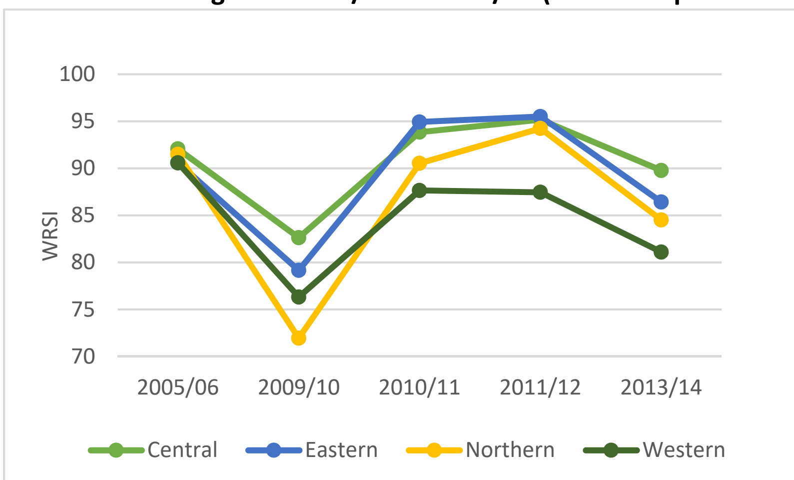
The availability of information, technical advice as well as proper functioning credit markets have been also identified as key factors for input use. Thus, we analyze whether adoption rates are higher among

[18] In a focus group with three groups of farmers in the Northern region (Gulu), farmers reported that poor weather conditions and low market price for their crops are two major sources of uncertainty and vulnerability for their livelihood. Uncertain outcomes and returns likely constrain the decision to adopt improved inputs, as the expected value is too ambiguous.

[19] The WRSI is calculated for each pixel using a maize crop model calibrated to the growing seasons across Uganda. Specifically, the geoWRSI v 3.0 was used with the global PET and RFE v2 (2001-2017) time series.

those who have been exposed to extension services and who have access to the financial markets. Figure 4.3 shows that inorganic fertilizer and pesticide use is slightly higher among those who live in a village in which extension services were available in the past 12 months,[20] and considerably higher in the case of improved seed use. Focus groups conducted by the authors with farmers in the Northern region of Uganda underlined that extension workers provide advice mainly on pesticide and hybrid seeds, and some actually expressed a belief that fertilizer may be harmful for the soil in the longer term.[21] While we do not have data on the exact content of the extension services provided to farmers, it may be important in determining the relative adoption rates among the different inputs considered in this study. Similarly, households that report having taken a formal loan also use pesticide at a higher rate, though not other agricultural inputs. This suggests that access to credit may not be a binding constraint in Uganda.

Figure 4.2: Weather conditions in Uganda 2005/06 to 2013/14 (Water Requirement Satisfaction Index)



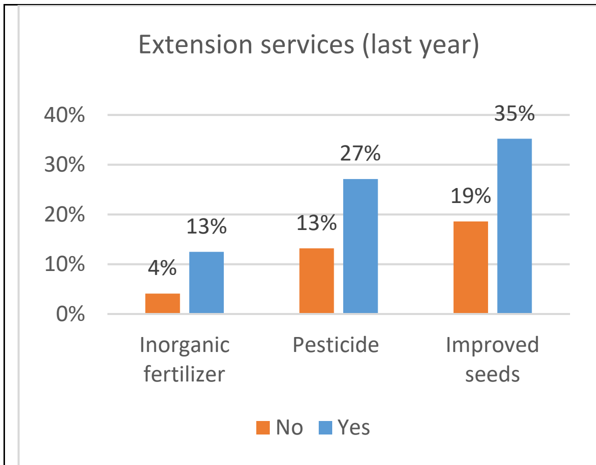
Source: Staff calculations staff calculations using geoWRSI v 3.0, with global PET and RFE v2 (2001-2017) time series.

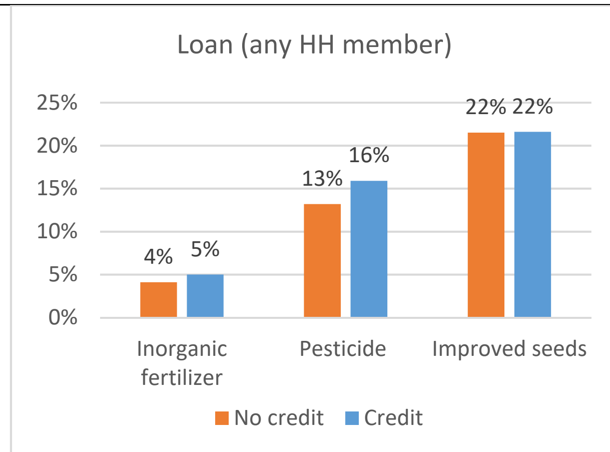
Figure 4.3: Input use seems higher among those with extension services and those taking formal credit

1. Extension	2. Credit

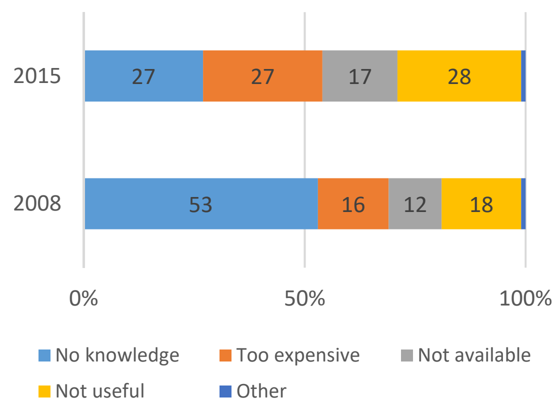
20 This includes extension services provided by NAADS (National Agricultural Advisory Services), input suppliers, NGOs and other institutions.

21 In June 2017, the authors met with members of farmer cooperative groups in Gulu and discussed how production practices had changed in recent years and why farmers did or did not use certain inputs.





3. Reasons for not using agricultural inputs



Source: 1-2: Staff calculations using UNPS 2005/06-2013/14, 3: NSDS 2015.

We estimate linear probability models to shed some light on the importance of the factors mentioned above on use of the following inputs: inorganic fertilizer, pesticide and improved seeds. This method allows us to consider the relationship between each of these factors— access to markets, rainfall, agricultural output prices, access to information and credit—at once and controlling for other factors. Household fixed effects control for time invariant unobservables at the household level that could impact adoption, which greatly reduces the threat of omitted variable bias. However, the latter is not sufficient to interpret our regressors effects as causal, as time variant unobservables factors could impact both adoption and the covariates. Examples of these are the household's social capital or farming ability. However, several of our main regressors of interest are largely outside the control of a small hold farming household: access to markets, weather conditions, and to a lesser extent, extension services and crop prices.

We model the decision to use inputs as:

$$y_{i,t} = \alpha + \beta X_{i,t} + \sigma Z_{i,t} + \mu_i + \epsilon_{i,t} \quad (1)$$

where $y_{i,t}$ is an indicator variable capturing household i's decision to use a given input (i.e. inorganic fertilizer, pesticide and hybrid seeds) at time t, $X_{i,t}$ is a vector of plot controls (area planted at time t, and land ownership of any planted parcel), $Z_{i,t}$ is a vector containing variables of interest including access to markets index, last crop season's value of the WRSI (proxy for optimal rainfall), availability and use of extension services, and last season's agricultural output price; μ_i is a household fixed effect, and $\varepsilon_{i,t}$ is an i.i.d normally distributed error term.

We consider the above specification using a balanced panel data set, that is, only households present in *all* five waves of the survey. We also consider a sub-sample of households in the bottom 40 percent of consumption expenditure distribution (the results can be found in the Appendix), to study how the results change when considering poor households.[22] Several specifications contain fewer than 5 years of data, because certain variables –such as access to financial loans – were no longer measured beyond the 2009/10 wave. It is worth noting that because the 2013 wave rotated out a considerable number of households, we are left with less than 1,000 households that are present in all 5 waves.

Several results emerge from the analysis. Enhanced access to economic markets marginally incentivizes input use among smallholder farmers in Uganda. Access to markets positively affects the decision to use both inorganic fertilizer and hybrid seeds, as observed in Tables 4.1 and 4.2. The effect is small, a 10 percent increase in the access to market index increases the probability of using inorganic fertilizer by about 0.01 percent. The result is robust under all specifications. The same is true in the case of hybrid seed use (see Table 4.2, albeit the coefficients are statistically significant only at the 10 percent level). The proximity to economic markets matters for input use both in terms of the availably and cost of the agricultural input *per se*, but also in terms of the feasibility and cost to sell the crop at the end of the season, which may increase the returns of adoption.

The weather conditions of the previous cropping season seem to matter slightly at the moment of deciding whether or not to adopt improved input for farmers in Uganda. The lagged value of the rainfall satisfaction index (WRSI) positively affects the adoption of inorganic fertilizer, pesticide and improved seeds. As with the access to market index, the magnitude of the effect is small: the regression analysis indicates that a 10 percent increase in rainfall sufficiency (in the previous season) results in a 0.1 percent increase in the inorganic fertilizer use, although the result is only statistically significant at 10 percent (see Table 4.1). In the case of pesticide, a 10 percent increase in rainfall sufficiency in the previous season results in an increase of 0.4 percent in adoption. The effect is also positive for hybrid seed use, and of approximately the same magnitude, as shown in Table 4.2. These results suggest that farmers are likely to consider that weather conditions of the current season will be similar to those in the previous season, and marginally tilt towards input adoption if the conditions were positive. An alternative explanation for the result observed is that good weather conditions in the previous season increases agricultural income, which allows the household to have enough liquidity to buy agricultural inputs for this season. However, when we control for the lag of the net agricultural income the results remain unchanged.[23]

Consistent with previous studies, we find that knowledge and information are positively correlated with improved input use in Uganda. The use of extension services in the household's community increases the probability of improved seed use by about 6 percentage points, and of pesticide use by slightly less (5 percentage points), but is not correlated with fertilizer, despite the high returns to the use of fertilizer documented in Section 3 (Tables 4.1 and 4.2). These findings not only indicate that information and

[22] The indicator takes a value of one if the household was in the bottom 40 percent of the distribution at any given wave of the panel. We also tried disaggregating the sample by region, but ended up underpowered to conduct any analysis.
[23] Results not reported in the main tables but available upon request.

guidance seem important to promote improved input use among smallholder farmers, but also underscore the importance of social networks and learning from peer farmers in spreading technology, as the recent literature has pointed out (see previous section). The fact that extension services are not correlated with the use of fertilizer may be linked to the content covered in advisory services and materials, and also to the prevalence of generic fertilizer recommendations that do not take into account prevailing soil conditions that should be measured appropriately through soil testing services (for both soil nutrient status and pH levels).

Given the historical importance of NAADS in the provision of agricultural extension services (and the fact that the Government of Uganda started to remove responsibilities away from NAADS after 2013), we ran a specification that includes an indicator variable if the household participated in a NAADS training in the last 12 months (second column in Tables 4.1 and 4.2). NAADS training is highly and positively correlated with every agricultural input studied in this paper. While it is not possible to argue that the training provided by NAADS causally increases input use among farmers, the results do suggest that these support services are important for farmers. It is also important to note that the smallest correlation is registered in the case of the use of fertilizer, which as mentioned before may be related to the content of the services provided and recommendations that do not reflect appropriate soil testing.

On the other hand, credit constraints do not appear to be binding for input adoption in Uganda, and past agricultural prices are not associated with the input adoption decision. Similarly, lagged prices of agricultural commodities do not seem to affect the farmer's decision to use improved inputs. It is possible that given the high variability of agricultural prices throughout the period 2005/06 to 2012/13 (see Figure 3.4), lagged prices were not a reliable predictor for prices for Ugandan farmers.

With respect to plot characteristics we find that the decision to use improved agricultural inputs is positively correlated with the self-reported area of the parcel planted, except for the adoption of hybrid seeds (Table 4.2). The result is in line with the findings of the agriculture production function literature, in which larger farms are more prone to experimentation and thus, to the adoption of improved inputs and modern technologies. On the other hand, we find no correlation between owning any of the land being cultivated and input use, despite the fact ownership is usually associated with a higher incentive to preserve the quality of the land, and thus with input adoption. While about 20 percent of farmers both own and rent at any given point in time, the little variation over time may help explain this result.

As mentioned above, we consider a subsample of households that belong to the bottom 40 of the consumption distribution (at any given point in time), to analyze if the results change for poor households. We find that enhanced access to markets and the availability of extension services in the community have no effect on input adoption, and we find a weakened effect of past weather conditions on pesticide and hybrid seeds (see Tables A.1 to A.3 in the Appendix). The only result that does not change is the high correlation between participating in a NAADs program and using improved inputs. Given the small number of observations for a fixed effects model, the analysis is likely underpowered to detect any significant effect or correlation. We encountered the same problem when trying to conduct the analysis by region.

Table 4.1 Correlates of Inorganic Fertilizer Use (2000 - 2012, balanced panel)

Inorganic Fertilizer	(1)	(2)	(3)	(4)
Log of distance to markets index, winsorized at 5%	0.00393***	0.00393***	0.00399*	0.00470***
	(0.000741)	(0.000691)	(0.00114)	(0.000528)
Log of WRSI for maize, lagged one period	0.121*	0.124*	0.0938	0.135
	(0.0516)	(0.0512)	(0.0575)	(0.0816)
Area of parcel planted in Ha, self-reported	0.00325**	0.00308**	0.00231*	0.00303**
	(0.000808)	(0.000765)	(0.000632)	(0.000881)
Household owns any of the land cultivated	-0.00294	-0.00445	-0.00376	-0.00428
	(0.0120)	(0.0112)	(0.0188)	(0.0174)
Use of any extension services in the community	0.0158		0.00804	0.0165
	(0.0127)		(0.0149)	(0.0157)
The household participated in a NAADs program		0.0377**		
		(0.0114)		
Any HH member obtained loan in past 12 months			0.00318	
			(0.0115)	
Average monthly real price of maize, lagged one period				0.000112
				(7.63e-05)
Constant	-0.512*	-0.527*	-0.387	-0.615
	(0.240)	(0.236)	(0.265)	(0.385)
Observations	3,045	3,045	1,902	1,813
R-squared	0.020	0.026	0.017	0.024

Table 4.2 Correlates of Pesticide and Improved Seed Use (2000 - 2012, balanced panel)

Pesticide	(1)	(2)	(4)	(5)
Log of distance to markets index, winsorized at 5%	0.000532	0.000429	0.000137	0.000405
	(0.00163)	(0.00145)	(0.00188)	(0.00222)
Log of WRSI for maize, lagged one period	0.360**	0.370**	0.273*	0.377*
	(0.0907)	(0.0828)	(0.0802)	(0.135)
Area of parcel planted in Ha, self-reported	0.0111***	0.0108***	0.00943***	0.0117**
	(0.00141)	(0.00132)	(0.000597)	(0.00203)
Household owns any of the land cultivated	-0.00688	-0.00933	-0.00108	-0.00475
	(0.0147)	(0.0167)	(0.0187)	(0.0214)
Use of any extension services in the community	0.0496*		0.0624*	0.0601
	(0.0204)		(0.0204)	(0.0320)
The household participated in a NAADs program		0.0895***		
		(0.0166)		
Any HH member obtained loan in past 12 months			0.0204	
			(0.0167)	
Average monthly real price of maize, lagged one period				-3.93e-07
				(0.000270)
Constant	-1.534**	-1.577**	-1.166*	-1.615*
	(0.403)	(0.367)	(0.360)	(0.598)
Observations	3,044	3,044	1,900	1,815
R-squared	0.066	0.073	0.065	0.078

Improved Seed	(1)	(2)	(3)	(4)
Log of distance to markets index, winsorized at 5%	0.00654*	0.00636*	0.00909*	0.00842
	(0.00284)	(0.00264)	(0.00263)	(0.00368)
Log of WRSI for maize, lagged one period	0.316**	0.326**	0.203	0.337*
	(0.0983)	(0.0886)	(0.0751)	(0.126)
Area of parcel planted in Ha, self-reported	0.00347	0.00323	0.00402	0.00588*
	(0.00188)	(0.00191)	(0.00261)	(0.00244)
Household owns any of the land cultivated	0.00582	0.00396	0.0137	-0.00887
	(0.0344)	(0.0297)	(0.0594)	(0.0323)
Use of any extension services in the community	0.0631***		0.0530**	0.0532**
	(0.0128)		(0.0109)	(0.0110)
The household participated in a NAADs program		0.0847***		
		(0.0184)		
Any HH member obtained loan in past 12 months			0.0411	
			(0.0277)	
Average monthly real price of maize, lagged one period				-0.000327
				(0.000192)
Constant	-1.261**	-1.295**	-0.746	-1.192
	(0.446)	(0.394)	(0.353)	(0.585)
Observations	2,979	2,979	1,906	1,784
R-squared	0.021	0.024	0.021	0.032

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions

Financial returns to input use in Uganda are considerable. This report analyzes some of the factors associated with the low input adoption observed in Uganda from 2005/06 to 2013/14. Despite favorable weather conditions and favorable agricultural crop prices, use rates of fertilizer, pesticide and hybrid seeds in Uganda remained stubbornly low throughout this period, particularly in comparison with other countries in Sub-Saharan Africa. We first analyze the financial returns to using inorganic fertilizer and improved seeds under normal conditions, across the distribution of observed prices in Uganda from 2000 onwards, along with yield parameters identified in the agronomic literature. The main finding is that financial gains from using inputs in Uganda are substantial, despite observed output price volatility. The economic return to fertilizer is always positive (across the entire price range) for beans, maize and matooke, and positive for the top 75 percent of prices for coffee. Median returns are 180 percent, 74 percent, 64 percent and 39 percent respectively. In the case of hybrid seeds, yields increased by 32 percent on average. However, the cost of using maize hybrid seeds often exceeds the extra revenue gained, reducing financial returns.

However, once the quality of inputs is considered, the returns decline substantially, becoming negative for a considerable segment of the price range. Given the substandard quality of inputs typically available in local markets, measured quantitively by several studies, the yield gain from using hybrid seeds and nitrogen falls by 75-87 percent. As a result, the sizable positive financial returns observed for using authentic inputs in maize crops disappear and even become negative at many prices. The rate of return on fertilizer is only positive when maize prices are in the top two-thirds of the distribution, and the median return drops from 64 percent to 20 percent. Given that farmers generally hold accurate beliefs about the quality of the inputs available on the local market, this is likely a disincentive to input adoption. Thus, increasing the quality of inputs available farmers would likely increase input adoption.

Strengthening the institutions that regulate input certification, promoting competition in input markets, and using new technologies may help improve the quality of inputs available in Uganda. Current regulation and certification measures are becoming effective at guaranteeing quality products in the agricultural input markets. Institutions regulating input quality control often lack the financial and technical resources to test the inputs found in markets, and, even when anomalies are detected, they lack the ability to effectively take actions that deter counterfeiting or malpractices (World Bank, 2018). Moreover, entry barriers, related to red-tape and permissions, restrict the competitiveness of input markets, particularly for fertilizers and new seed varieties (Benson et al 2013). Strengthening the institutions that regulate certification and enhancing competition in input markets could result in quality improvements. Moreover, the introduction of new technologies, such as e-verification, could also help to insure the average farmer has access to high quality agricultural inputs. This tool, which involves labeling genuine agricultural inputs with a scratch-off label, which reveals an authentication code, can be used via SMS and is currently being piloted in Uganda. If the results of the pilot are positive, this might be an option worth scaling at the national level (IFPRI 2015).

Access to markets and weather are marginally relevant in the farmer's decision to adopt improved inputs. Our results suggest that increased access to economic markets, and (good) past weather conditions marginally increase input use (inorganic fertilizer and hybrid seeds). Similarly, weather conditions of the previous cropping season seem to weakly impact the decision adopt improved inputs. The results underline the importance of investing and maintaining road networks that connect rural farmers to economic markets. While many other interventions are necessary to increase input use in Uganda, the current efforts of the Government of Uganda to integrate rural areas to economic markets are a step in the right direction.

Extension training and knowledge seem to be a key factor in the use of improved inputs, and strengthening these services is a critical area of action. We find that the use of extension services in households' communities (and particularly of those provided by NAADS) is highly correlated with the use of the inputs studied here, except for the use of fertilizer. That is why one aspect of the extension services that deserves more attention is whether the content of the services provided could be more effective in promoting the use of fertilizer, which is crucial for soil quality in the long run, particularly when hybrid seeds are being utilized. Also, fertilizer recommendations should be based on appropriate soil testing (for both soil nutrients and pH levels) to avoid generic recommendations that may not produce the expected results. Ugandan famers would benefit greatly if public resources are directed towards the generation and provision of knowledge and advisory services to farmers, rather than towards the procurement and distribution of material inputs, as has been the case since 2013.

References

Berg, Claudia N.; Blankespoor, Brian; Selod, Harris. 2016. Roads and rural development in Sub-Saharan Africa. Policy Research working paper; no. WPS 7729. Washington, D.C.: World Bank Group.

Anderson, J. R., & Feder, G. (2007). Chapter 44 Agricultural Extension. *Handbook of Agricultural Economics*, *3*(6), 2343–2378.

Ashour, M., Billings, L., Gilligan, D., & Hoel, J. (2016). *Do Beliefs About Agricultural Inputs Counterfeiting Correspond with Actual Rates of Counterfeiting? Evidence from Uganda* (IFPRI No. 1552).

Bandiera, O., & Rasul, I. (2006). Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal*, 116(514), 869–902.

Bandiera, O., Burgess, R., Morel, R., Rasul, I., & Sulaiman, M. (2015). *A randomized evaluation of the combined effect of an extension agriculture programs and a microfinance program in rural Uganda*.

Barham, B. L., Chavas, J., Fitz, D., Ríos, V., & Schechter, L. (2014). The roles of risk and ambiguity in technology adoption. *Journal of Economic Behavior and Organization*, 97, 204–218.

Barrett, C. B., Christiaensen, L., Sheahan, M., & Shimeles, A. (2017). *On the Structural Transformation of Rural Africa* (World Bank No. 7938).

Berg, Claudia N.; Blankespoor, Brian; Seod, Harris. 2016. Roads and rural development in Sub-Saharan Africa. Policy Research working paper; no. WPS 7729. Washington, D.C.: World Bank Group.

Binswanger, H. P. (1980). Agricultural & Applied Economics Association Attitudes toward Risk : Experimental Measurement In Rural India. *Agricultural Journal of Agricultural Economics*, 62(3), 395–407.

Binswanger-Mkhize, H. P., & Savastano, S. (2014). *Agricultural Intensification The Status in Six African Countries*. *Food Policy*, *67, 26-40.*

Birkhaeuser, D., Evenseon, R., & Feder, G. (2017). The Economic Impact of Agricultural Extension : *Economic Development and Cultural Change*, 39(3), 607–650.

Blankespoor, Brian; Khan, Amjad; Selod, Harris. In prep. Consolidating Data of Global Urban Populations: A Comparative Approach. Geospatial Analysis for International Development Conference, UC-Berkeley. Poster.

Boef, W. De, Pierson, B., Kim, D., Mennel, J., Prabhala, P., Bryce, J., Hoffman, A. (2014). *Counterfeiting in African Agriculture Inputs – Challenges & Solutions Ghana: Overview*.

Boserup, E. ,1965, Population and technological change: A study of long-term trends, University of Chicago Press, Chicago.

Bold, T., Yanagizawa-Drott, D., Kaizzi, K., & Svensson, J. (2017). Lemon Technologies and Adoption: Measurement, Theory and Evidence from Agricultural Markets in Uganda. *Quarterly Journal of Economics*.

Brauw, A. De, & Eozenou, P. (2014). Measuring risk attitudes among Mozambican farmers ☆. *Journal of Development Economics*, 111, 61–74.

Cafiero, C., Bobenrieth, S. A., & Wright, B. D.. (2005) “Commodity storage and the autocorrelation of prices”, Mimeo, Berkley.

Campenhout, B. Van, Vandevelde, S., Walukano, W., & Asten, P. Van. (2017). Agricultural Extension Messages Using Video on Portable Devices Increased Knowledge about Seed Selection, Storage and Handling among Smallholder Potato Farmers in Southwestern Uganda. *PLOS One*, 1–17.

Carletto, G., & Bank, W. *Rural Income Generating Activities (RIGA) Study: Income Aggregate Methodology*.

Cole, S. a, & Fernando, a N. (2012). *The Value of Advice: Evidence from Mobile Phone-Based Agricultural Extension*.

Conley, B. T. G., & Udry, C. R. (2016). Learning about a New Technology : Pineapple in Ghana. *The American Economic Review*, 100(1), 35–69.
Croppenstedt, A., Demeke, M., & Meschi, M. M. (2003). Technology Adoption in the Presence of Constraints : the Case of Fertilizer Demand in Ethiopia. *Review of Development Economics*, *7*(1), 58–70.
Deaton and Laroque (2003). “A model of commodity prices after Sir Arthur Lewis,” *Journal of Development Economics*, 71, 289–310.
Dercon, S., Gilligan, D. O., Hoddinott, J., & Woldehanna, T. (2017). The Impact of Agricultural Extension on Poverty and Consumption Growth in Fifteen Ethiopian Villages. *American Journal of Agricultural Economics*, 91(4).
Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics*, 96(2), 159–173.
Diiro, G. M., & Sam, A. G. (2015). Agricultural technology adoption and Nonfarm earnings in Uganda: A semi parametric analysis. *Journal of Developing Areas*, 49(2), 145–162.
Donaldson, D. (forthcoming) Railroads and the Raj: Estimating the impact of transportation infrastructure. American Economic Review, in press.
Dorfman, J. H. (1996). Modeling Multiple Adoption Decisions in a Joint Framework. *American Journal of Agricultural Economics*, 78(3), 547--557.
Duflo, B. E., Kremer, M., & Robinson, J. (2011). Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya, *American Economic Review*, 101(6), 2350–2390.
Esilaba, A. O., Nyende, P., Nalukenge, G., & Byalebeka, J. B. (2005). Resource flows and nutrient balances for crop and animal production in smallholder farming systems in eastern Uganda, 109, 192–201.
Evenson, R. E., & Mwabu, G. (1998). The Effect of Agricultural Extension on Farm Yields in Kenya. *African Development Review*, 13(1), 1–23.
Fafchamps, M., and Hill, R. V. (2005). "Selling at the Farmgate or Traveling to Market" *American Journal of Agricultural Economics*, Agricultural and Applied Economics Association, vol. 87(3), pages 717-734.
Fafchamps, M., & Minten, B. (2012). Impact of SMS-based agricultural information on Indian farmers. *World Bank Economic Review*, 26(3), 383–414.
Fairbairn, A., Michelson, H., Ellison, B., & Manyong, V. (2016). *When Lemons Aren’t Lemons: Fertilizer Quality and Farmer Perceptions in Tanzania*. University of Illinois Working Paper.
Feder, G., Just, R., & Zilberman, D. (2017). Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change*, 33(2), 255–298.
Foster, A. D., Rosenzweig, M. R., (2013). Learning by Doing and Learning from Others : Human Capital and Technical Change in Agriculture. *Journal of Political Economy*, 103(6), 1176–1209.
Gollin, D., & Moser, S. (2013). Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? *American Journal of Agricultural Economics, 96(1), 308–327.*
Hall, B. H., & Khan, B. (2003). Adoption of New Technolgoy. *NBER Working Paper 9730*, (May).
Harou, A., & Barrett, C. B. (n.d.). Variable Returns to Fertilizer Use and Its Relationship to Poverty Experimental and Simulation Evidence from Malawi. *Journal of African Economies*, (September).
Hellerstein, D., Higgins, N., & Horowitz, J. (2013). The predictive power of risk preference measures for farming decisions. *European Review of Agricultural Economics*, 40(5), 807–833.
Hennessy, D. A. (1997). Stochastic technologies and the adoption decision. *Journal of Development Economics*, 54(2), 437–453.

Hill, R., & Meija-Mantilla, C. (2016). With a Little Help Shocks, Agricultural Income, and Welfare in Uganda. *World Bank Policy Research Papers, No. 7935*.

IFPRI (2015). Baseline evaluation of the impact of e-verification on counterfeit agricultural inputs and technology adoption in Uganda. International Food Policy Research Institute (IFPRI).

Incus, P., Ingh, J. U. S., Allejos, C. E. D. V, Tjernstrom, E., Clavijo, J., Bhakta (2017). When Intentions Matter – Identifying the Prevalence and Source of Poor-Quality Inputs in Western Kenya. *International Consortium on Applied Bioeconomy Research*.

Jack, Kelsey B. (2011). Market inefficiencies and the adoption of agricultural technologies in developing countries. *White Paper, Agricultural Technology Adoption Initiative*, 1–69.

Janvry, A. De, Sadoulet, E., & Suri, T. (2017). *Field Experiments in Developing Country Agriculture*. *Handbook of Economic Field Experiments* (Vol. 2).

Jedwab, Remi; Storeygard, Adam (2015). The Heterogeneous Effects of Transportation Investments: Evidence from sub-Sub-Saharan Africa. mimeo, presented at the GWU/World Bank 3rd Urbanization and Poverty Reduction Research Conference (February 1, 2016).

Just, R. E., & Zilberman, D. (1983). Stochastic Structure, Farm Size and Technology Adoption in Developing Agriculture. *Oxford Economic Papers*, 35(2), 307–328.

Kaizzi, K. C., Byalebeka, J., Semalulu, O., Alou, I., Zimwanguyizza, W., Nansamba, A. Wortmann, C. S. (2012). Maize response to fertilizer and nitrogen use efficiency in Uganda (2012a). *Agronomy Journal, 104(1), 73–82.*

Kaizzi, K. C., Byalebeka, J., Semalulu, O., Alou, I., Zimwanguyizza, W., Nansamba, A., Wortmann, C. S. (n.d.). Sorghum Response to Fertilizer and Nitrogen Use Efficiency in Uganda (2012b). *Agronomy Journal*, 104(1).

Kaizzi, K. C., Byalebeka, J., Semalulu, O., Newton, I., Zimwanguyizza, W., Nansamba, A., Wortmann, C. S. (2012c). Field Crops Research Optimizing smallholder returns to fertilizer use: Bean, soybean and groundnut. *Field Crops Research*, 127, 109–119.

Kasirye, I. (2013). Constraints to Agricultural Technology Adoption in Uganda: Evidence from the 2005/06-2009/10 Uganda National Panel Survey. Economic Policy Research Centre (EPRC), Kampala, Uganda.

Kim, T.-K., Hayes, D. J., & Hallam, A. (1992). Technology adoption under price uncertainty. *Journal of Development Economics*, 38, 245–253.

Kondylis, F., Mueller, V., & Zhu, S. (2017). Seeing is Believing? Evidence from an Extension Network, *Journal of Development Economics*, 125, 1–20.

Koundouri, P., Nauges, C., & Tzouvelekas, V. (2016). Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology. *American Journal of Agricultural Economics*, *88*(3).

Krishnan, P., & Patnam, M. (2013). Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? *American Journal of Agricultural Economics*, 96(1), 308–327.

Maertens, A., & Barrett, C. B. (2012). Measuring Social Networks' Effects on Agricultural Technology Adoption. *American Journal of Agricultural Economics*, 95(2), 353–359.

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty impedes cognitive function. *Science*, 341(6149), 976–80.

Manski, C. F. (1993). Identification of Endogenous Social Effects : The Reflection Problem. *The Review of Economic Studies*, 60(3), 531–542.

McCarthur, J. W., and McCord, G. (2017). Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics*, 127, 133-152.

Mobarak, A. M., & BenYishay, A. (2017). Social Learning and Communication. *Review of Economics Studies,forthcoming*.

Munshi, K. (2004). Social learning in a heterogeneous population : technology diffusion in the Indian Green Revolution. *Journal of Development Economics*, 73, 185–213.

Mullally, C., Boucher, S., & Carter, M. (2013). Encouraging Development: Randomized Encouragement Designs in Agriculture. *American Journal of Agricultural Economics*, *95*(5), 1352–1358.

Ngome, A. F., Becker, M., Mtei, K. M., & Mussgnug, F. (2013). Fertility management for maize cultivation in some soils of Western Kenya. *Soil & Tillage Research*, 117(2011), 69–75.

Nkonya, E., Kaizzi, C., & Pender, J. (2005). Determinants of nutrient balances in a maize farming system in eastern Uganda. *Agricultural Systems*, 85(2), 155–182.

Nyombi, K., Asten, P. J. A. Van, Corbeels, M., Taulya, G., Leffelaar, P. A., & Giller, K. E. (2010). Mineral fertilizer response and nutrient use efficiencies of East African highland. *Field Crops Research*, 117(1), 38–50.

Okech, S.H., van Asten, P. J., Gold, C.S., & Ssali, H. (2004). Effects of potassium deficiency , drought and weevils on banana yield and economic performance in Mbarara, Uganda. *Uganda Journal of Agricultural Sciences,* 9, 511 – 519.

Rogers, E. M., & Everett, M. (1962). Diffusion of Innovations*, Third Edition*. New York: Macmillan Publishing.

Ruthenberg, H. P. ,1980, Farming Systems in the Tropics, Oxford: Clarendon.

Sanders, J. H., Shapiro, B. I., & Ramaswamy, S. (1996). *The economics of agricultural technology in semiarid Sub Saharan Africa*. Baltimore: Johns Hopkins University Press.

Sheahan, M., & Barrett, C. B. (2017). Understanding the Agricultural Input Landscape in Sub-Saharan Africa Recent Plot, Household , and Community-Level Evidence. *Food Policy,*, 67, 12-25.

Sileshi, G., Akinnifesi, F. K., Debusho, L. K., Beedy, T., Ajayi, O. C., & Mong, S. (2010). Variation in maize yield gaps with plant nutrient inputs , soil type and climate across sub-Saharan Africa. *Field Crops Research*, 116, 1–13.

Spielman, D. J., Kelemwork, D., & Alemu, D. (2011). *Seed, Fertilizer, and Agricultural Extension in Ethiopia*.

Sserunkuuma, D. (2005). The Adoption and Impact of Improved Maize and Land Management Technologies in Uganda. *Journal of Agricultural and Development Economics*, *2*(1), 67–84.

Sunding, D., & Zilberman, D. (2001). The agricultural innovation Process: Research and technology adoption in a changing agricultural sector. *Handbook of Agricultural Economics*, (1999).

Suri, T. E. (2011). Selection and Comparative Advantage in Technology Adoption. *Econometrica*, *79*(1), 159–209.

Tsur, Y., Sternberg, M., & Hochman, E. (2016). Dynamic Modelling of Innovation Process Adoption with Risk Aversion and Learning. *Oxford Economic Papers*, *42*(2), 336–355.

Van Asten, D., Ochala, M., & Wairegi, L. (2017). Agronomic and Economic Benefits of Urea Fertilizer Application in Coffee Mono-crop and coffee-banana intercrop systems. Working Paper. International Institute of Tropical Agriculture.

Vasilaky, K. N., & Leonard, K. L. (2017). As Good as the Networks They Keep?: Improving Outcomes through Weak Ties in Rural Uganda. *Economic Development and Cultural Change*, 66(4), 755-792..

World Bank, 2016. “Farms, cities and good fortune: assessing poverty reduction in Uganda from 2006 to 2013”. Poverty and Equity practice, Africa region. Washington DC, World Bank Group.

Appendix

Estimation of financial returns

Yields are projected using the coefficients from estimated asymptotic quadratic-plus-plateau yield functions taken from a variety of field studies. These coefficients were compiled into a response function database (Ofra 2017). The estimates come from fitting an asymptotic quadratic–plateau function, which gives an exponential rise to maximum yield. The asymptotic function for nitrogen is $a - bc^N$, where a, b, and c are estimated as N varies across field tests. The Fertilizer Optimization Tool, a projection tool parameterized using the Ofra (2017) database of field studies, can then generate yield responsiveness and returns given a budget constraint and prices, as in Figure 3.2.

The optimal fertilizer application rates were lower for beans than for maize (45 kg per hectare as opposed to 108 kg per hectare), and used less costly seed (4,500 Ugandan shillings per kg as opposed to 7,000 Ugandan shillings per kg for maize).

We use the price for fertilizer and seed costs as stated in each study or confirmed via local distributors in Uganda. Since the various studies took place in different years, we deflate all prices using the 2005 CPI. Seed application rates per hectare were calculated from the targeted plant growth per meter squared and estimated using the seed's weight.[24] Fertilizer application rates varied based on the study used for each crop's return and are listed below.

Returns to nitrogen for maize were taken from Bold et al. (2017). Returns to nitrogen for beans were taken from K.C. Kaizzi et al. (2012), and the estimates themselves were pulled from the OFRA Response Function Database (Wortmann 2017). Returns to NPK for matooke were taken from Nyomibi et al. (2010), and the estimates themselves were pulled from the OFRA Response Function Database (Wortmann 2017). Returns to nitrogen for Robusta coffee were taken from Asten et al. (2011). The OFRA Response Function Database compiles 254 studies, which estimate the returns for various inputs. Because the database provides the estimated parameters to the inputs return function, we can choose the amount of fertilizer to input to calculate the yield response. For beans and matooke we use 45 kilograms of fertilizer per hectare, the middle fertilizer value explored in these studies. Conversely, for maize and coffee, the corresponding studies only provide average returns for one set of input values, which correspond to official recommendations for authentic urea.

We assume that traditional seed prices cost approximately one-third of improved or hybrid seed.[25] Though in some cases, traditional seed may very well be free.[26] Returns per hectare as compared to a control group (no hybrid seed, no fertilizer) to inputs were calculated by using the following formula:

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[24] For example, if the targeted plant growth was 11 plants per square meter, then that is 11 seeds per square meter multiplied by the weight of the seed to estimate how many kilograms of seed were used per hectare. For example, a 100 seed bag of K132 beans is 35 grams.

[25] Note that only the Bold et al (2017) study applies hybrid seed, while all other studies use improved seed, including the households in the LSMS.

[26] The returns can vary based on our assumptions relating to traditional seed costs. There is inadequate data as to whether farmers are purchasing traditional seed and at what price. Here we assume a traditional seed price that is 30% of hybrid or improved seed prices. For matooke and coffee we do not consider seed costs, assuming that trees have already been planted in the past.

$$\frac{\Delta y * p^q - l^{fs} * (c_f + c_s)}{l^{fs} * (c_f + c_s)}$$

where Δy is the change in yield per hectare as compared to control plots, p^q is the farm gate output price of the commodity for the q[th] price quintile, c_f is fertilizer cost or total fertilizer used per hectare times its cost, and c_s is seed cost or total seed used per hectare times its cost, l^{fs} is an additional labor factor that is 1.47 whenever hybrid varieties are used – a factor taken from Bold et al. (2016).[27] The extra labor is needed for the more intensive application of fertilizer for hybrid varieties.

Seed application rate for maize was backed out in terms of kilograms per hectare, and computed for beans based on the number of plants cultivated per hectare. Coffee and matooke do not require seeds after the tree has already been planted. Seed prices were taken from the cited studies and cross checked with online retailers. Nitrogen fertilizer price was also taken from the Bold et al. (2017) study, but agreed with the other studies cited here (~3,000 Uganda shillings per kilogram).

All prices were deflated to 2005 prices with a CPI index. In all cases, but coffee, our output price data was multiplied by a factor of ~ 0.7. We found that the ratio of farm gate prices as compared to our international price data was approximately 0.6 - 0.8. With coffee, our price data for unmilled coffee was on par with farm gate prices, and, therefore, not deflated.

We then calculate returns across years 2005 to 2012 for median and mean output prices by region and quintile (Central, Eastern, Western, Northern) and then averaged returns across all years. Input prices were kept constant. Thus, we are interested in how the potential increased yield benefits farmers, on average, given constant, yet representative, input costs.

As an example for maize:

We calculated returns at the 5, 25, 50, 75, and 90 percentile of output prices. The return at the 50[th] percentile of maize prices in the East for authentic fertilizer and authentic hybrid seed after deflating to 2005 prices:

$$\frac{(0.6*284)\,{}^{shs}/_{kg} * 3{,}617\,{}^{kg}/_{ha} - 1.47(1{,}393\,{}^{shs}/_{kg} * 108\,{}^{kg}/_{ha} + (0.6*3{,}250)\,{}^{shs}/_{kg} * 50\,{}^{kg}/_{ha})}{1.47(1{,}393\,{}^{shs}/_{kg} * 108\,{}^{kg}/_{ha} + (0.6*3{,}250)\,{}^{shs}/_{kg} * 50\,{}^{kg}/_{ha})}$$

Where we know that the return of 3,617 kilograms per hectare because the return to authentic fertilizer and authentic hybrid seed from Bold et al. (2017) is (2.60 + 46*0.065) tonnes per hectare, and the baseline return (no fertilizer, no hybrid seed) is 1.973 tonnes per hectare.

[27] Costs are 32% more for applying fertilizer (Bold et al 2017), so 32% of the total input expenses, per hectare , implies that $l^{fs} = 0.32 * (c_f + c_s + l^{fs})$ or $l^{fs} = 0.47 * (c_f + c_s)$.

The following list the input values used for each crop.

Maize (N)	change yield kgs/ha	fertilizer price shs/kg	fertilizer amount kg/ha	seed cost shs/kg	seed amount kgs/ha	deflation output price factor
AUTHENTIC FERTILIZER N WITH AUTHENTIC HYBRID SEEDS	3617	3000	108	7000	50	0.7
AUTHENTIC FERTILIZER N	2254	3000	108	7000	50	0.7
AUTHENTIC HYBRID SEEDS	627	3000	108	7000	50	0.7
INAUTHENTIC FERTILIZERN WITH INAUTHENTIC HYBRID SEEDS	2108	3000	108	7000	50	0.7
INAUTHENTIC FERTILIZER N	1558	3000	108	7000	50	0.7
INAUTHENTIC HYBRID SEEDS	295	3000	108	7000	50	0.7

Beans (N)	change yield kgs/ha	fertilizer price shs/kg	fertilizer amount kg/ha	seed cost shs/kg	seed amount kgs/ha	deflation output price factor
AUTHENTIC FERTILIZER N WITH AUTHENTIC IMPRPOVED SEEDS	1718	3000	45	4500	85	0.6
AUTHENTIC FERTILIZER N	840	3000	45	4500	85	0.6
AUTHENTIC IMPROVED SEEDS	787	3000	45	4500	85	0.6

Matooke (NPK)	change yield kgs/ha	fertilizer price shs/kg	fertilizer amount kg/ha	seed cost shs/kg	seed amount kgs/ha	deflation output price factor
AUTHENTIC FERTILIZER NPK	1000	3000	45	0	0	0.8

Coffee (N)	change yield kgs/ha	fertilizer price shs/kg	fertilizer amount kg/ha	seed cost shs/kg	seed amount kgs/ha	deflation output price factor
AUTHENTIC FERTILIZER N	1040	3000	190	0	0	1

Construction of the market access variable

The market access (MA) index combines road data for three years, due to the availability of geo-referenced road data (2004, 2010 and 2013), population data, and household panel data from the UNPS

(2005, 2009, 2010 and 2011). In order to construct the MA index, we combined the city population data of 101 cities above 10,000 people from an urban population database developed by Blankespoor et al. (in prep) with the roads panel derived from Uganda National Roads Authority (UNRA), which provides geo-referenced information on road categories, surface type and condition.

The indicator uses the network-enabled geometry of DeLorme (2009) road data for Uganda and nearby roads from adjacent countries with attribute information from the UNRA. A region-wide road network for each household year is constructed by considering the road segments and associated functional classes available for the closest date to that year from roads data from UNRA.[28] For each household year t, travel times $\tau_{ij,t}$ between any two pairs of nodes (i and j) on the reconstructed region-wide road network. The geometry of the urban population data was modified to ensure that each populated place was associated with the nearest node on the reconstructed region-wide road network, yielding the population measure $P_{j,t}$ for each node j. Likewise, the offset coordinates provided by UNPS were associated with the nearest node on the region-wide road network, yielding the origin location for each year, t, and for each household coordinate, *i*. It then became possible to calculate the market access index for all nodes according to Formula (1).

Following Donaldson (forthcoming), the elasticity of trade, θ, is equal to 3.8. Different values of the trade elasticity parameter provide alternative results for robustness checks (e.g. see Jedwab and Storeygard 2015; and Blankespoor et al. 2016).

[28] The following road data are used in the travel time model: road categories from DeLorme (Primary, Secondary and Tertiary); road surface type (paved and non-paved) and road surface condition (very good, good, fair, poor and very poor).

Tables

Table A.1 Correlates of Inorganic Fertilizer Use for Bottom 40 percent (2000 - 2012, balanced panel)

	(1)	(2)	(3)	(4)
Log of distance to markets index, winsorized at 5%	0.00156	0.00165	0.00368	0.00218
	(0.00159)	(0.00158)	(0.00153)	(0.00202)
Log of WRSI for maize, lagged one period	0.0791	0.0799	0.0504	0.0605
	(0.0381)	(0.0394)	(0.0384)	(0.0400)
Area of parcel planted in Ha, self-reported	0.00277	0.00270	0.00170	0.00242
	(0.00142)	(0.00141)	(0.00178)	(0.00156)
Household owns any of the land cultivated	0.00495	0.00433	0.00650	0.0122
	(0.00984)	(0.00994)	(0.0156)	(0.00567)
Use of any extension services in the community	-0.000418		-0.00652	-0.0126
	(0.00640)		(0.00506)	(0.00609)
The household participated in a NAADs program		0.0177		
		(0.0141)		
Any HH member obtained loan in past 12 months			-0.00313	
			(0.00854)	
Average monthly real price of maize, lagged one period				0.000146
				(7.31e-05)
Constant	-0.343	-0.349	-0.207	-0.319
	(0.174)	(0.180)	(0.174)	(0.160)
Observations	1,371	1,371	870	866
R-squared	0.016	0.018	0.015	0.024

Table A.2 Correlates of Pesticide Use for Bottom 40 percent (2000 - 2012, balanced panel)

	(1)	(2)	(4)	(5)
Log of distance to markets index, winsorized at 5%	0.000270	0.000600	-0.00157	-0.00133
	(0.00181)	(0.00198)	(0.00105)	(0.00127)
Log of WRSI for maize, lagged one period	0.203**	0.211**	0.142	0.232*
	(0.0726)	(0.0691)	(0.0589)	(0.0783)
Area of parcel planted in Ha, self-reported	0.00933***	0.00921***	0.00771**	0.0119**
	(0.00173)	(0.00172)	(0.00111)	(0.00280)
Household owns any of the land cultivated	0.0387**	0.0379**	0.0217**	0.0289*
	(0.0115)	(0.00982)	(0.00381)	(0.0102)
Use of any extension services in the community	0.0165		0.0309	0.0265
	(0.0151)		(0.0218)	(0.0215)
The household participated in a NAADs program		0.0632**		
		(0.0184)		
Any HH member obtained loan in past 12 months			0.0222	
			(0.0396)	
Average monthly real price of maize, lagged one period				0.000277
				(0.000326)
Constant	-0.876*	-0.913**	-0.612	-1.123*
	(0.336)	(0.323)	(0.279)	(0.401)
Observations	1,370	1,370	868	867
R-squared	0.041	0.047	0.040	0.065

Table A.3. Correlates of Improved Seed Use (2000 - 2012, balanced panel)

	(1)	(2)	(3)	(4)
Log of distance to markets index, winsorized at 5%	-0.00323	-0.00295	-0.00356	-0.00277
	(0.00236)	(0.00227)	(0.00372)	(0.00465)
Log of WRSI for maize, lagged one period	0.234*	0.245*	0.171	0.219**
	(0.0971)	(0.0901)	(0.133)	(0.0628)
Area of parcel planted in Ha, self-reported	0.00308	0.00315	0.00467	0.00596
	(0.00267)	(0.00280)	(0.00329)	(0.00322)
Household owns any of the land cultivated	0.0268	0.0278	0.0390	0.0147
	(0.0210)	(0.0209)	(0.0364)	(0.0379)
Use of any extension services in the community	0.0452		0.0238	0.0376
	(0.0257)		(0.0165)	(0.0245)
The household participated in a NAADs program		0.0541**		
		(0.0179)		
Any HH member obtained loan in past 12 months			0.0357	
			(0.0427)	
Average monthly real price of maize, lagged one period				0.000220
				(0.000454)
Constant	-0.952*	-0.991*	-0.665	-0.946
	(0.434)	(0.401)	(0.604)	(0.458)
Observations	1,359	1,359	871	853
R-squared	0.015	0.015	0.017	0.019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1