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Understanding the dynamics of adoption decisions and their poverty impacts

The case of improved maize seeds in Uganda

by
Alessandra Garbero
Pierre Marion

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Authors:
Alessandra Garbero, Pierre Marion

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About the authors

Alessandra Garbero is Senior Econometrician in the Research and Impact Assessment Division, Strategy and Knowledge Department, IFAD. Her work focuses on impact assessment methodologies and applied econometrics in developing regions. She obtained her PhD from the London School of Hygiene and Tropical Medicine. Her thesis was a methodological assessment of the implications of different econometric methods used in the relevant literature to estimate the impact of adult deaths. Her first degree was in economics, and she specialized in demography and research methods. Her previous work experience involved working at the United Nations Population Division on population projections, and at the Food and Agriculture Organization of the United Nations on the impact of HIV and AIDS on food security and agriculture, as well as on the improvement of the collection, dissemination and use of gender-disaggregated data in agriculture and rural development. She also developed a methodology to evaluate the impact of HIV and AIDS on the agricultural labour force. Before joining IFAD, she was a research scholar at the International Institute for Applied Systems Analysis, where she was part of a team of analysts working on analytical, methodological and modelling research.

Pierre Marion is a research analyst at the University of Oxford in the Young Lives Study (Oxford Department of International Development). Previously, he worked for the Research and Impact Assessment Division, Strategy and Knowledge Department, IFAD. He is specialized in impact assessments and agriculture research. His research interests are in the areas of poverty, vulnerability, food security, agriculture and rural development. He has worked on impact assessments in Chad, Ethiopia, Senegal, Uganda and United Republic of Tanzania. Prior to IFAD, he was part of the Statistics Division at the Food and Agriculture Organization of the United Nations. He completed an MSc in development economics at the University of Sussex, United Kingdom.

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Abstract

The present study estimates the impact of agricultural research, specifically that of improved varieties of maize seeds on agricultural productivity and welfare in Uganda using a panel survey covering three years. We first examine the determinants of technology adoption in a dynamic setting that allows for state dependence in the adoption decision process. The analysis shows that previous adoption is highly important in explaining contemporary adoption. We then evaluate the impact of the adoption of improved maize seeds on welfare, notably consumption-expenditure, poverty, and agricultural outcomes such as yields. Based on a review of the adoption literature, which stresses the need to consider both the endogeneity of the adoption decision process and selection due to both observable and unobservable features, we compare the robustness of a number of estimators in order to present credible results. Estimators range from Heckman selection and endogenous switching regression to a control function approach combined with correlated random effects for binary poverty outcomes (namely the poverty headcount) and fixed effects, which are instead suitable for continuous poverty outcomes and agricultural outcomes. In addition, we combine a control function approach with both correlated random effects and double-hurdle models for variables that present a non-linear corner solution, namely improved maize yields and value of production from improved maize seeds. Last, we relax the hypothesis of homogeneity in returns and use a correlated random coefficient model to further explore whether returns to adoption are correlated with the individual choice to adopt over time and are, therefore, heterogeneous.

Strong statistically significant positive impacts are found both across agricultural productivity and consumption expenditure and poverty indicators. We find that the magnitude of impacts is fairly similar across the different models. Estimates for the daily per adult equivalent expenditure increase by 5-16 per cent as a result of agricultural technology (total agricultural production increase by 5-13 per cent), and the proportion of poor (set with a daily per capita poverty threshold of US$2 purchasing power parity [PPP]) decreases by 4-12 per cent. We find that poverty reduction occurs through a rise in maize yields, where adoption of improved maize seeds increases the value of production. However, while we find that adoption history does not influence returns on yields, it does affect poverty reduction outcomes. Here, the pattern of the adoption decision process seems to influence the extent of poverty reduction, implying that farmers may switch in and out of the technology to maximize their welfare gains or simply avoid losses in the presence of shocks. Shocks leading to a fall in the returns from improved maize, such as a decline in the price of maize, a reduction in household maize output, or a rise in the price of improved maize seeds, could explain this heterogeneity in the poverty impacts and farmers' switching behaviour.

One major policy recommendation arising from this study is that extension services should be better suited to addressing the volatility of the agricultural context where smallholders operate. Such extension support needs to be more timely, and tailored to the local context and the needs of rural smallholders in order to properly address their vulnerability and liquidity constraints, which prevent them from fully making a long-term profit from the unequivocal benefits of this technology.

Abbreviations and acronyms

ATT	average treatment effect on the treated
ATU	average treatment effect on the untreated
CF	control function (approach)
CRC	correlated random coefficient (model)
CRE	correlated random effects
DH	double-hurdle (model)
ESRM	endogenous switching regression model
FE	fixed effect
ISA	Integrated Surveys on Agriculture
IV	instrumental variable
LSMS	Living Standard Measurement Survey
NAADS	National Agricultural Services
NARO	National Agricultural Research Organisation
NERICA	New Rice for Africa
PL	poverty line
PPP	purchasing power parity
PSM	propensity score matching

1 Introduction

Agricultural research has played a key role in improving rural livelihoods in the developing world, with substantial pro-poor impacts of international agricultural R&D materializing over time (Adato and Meinzen-Dick, 2007; Thirtle and Piesse, 2003). Given that research and technological improvements are important factors in increasing agricultural productivity and reducing poverty in developing countries (Alston et al., 2000), understanding adoption of technological change in agriculture and its impact on poverty dynamics is a topic that continues to receive attention in the development literature (de Janvry and Sadoulet, 2002; de Janvry, 2010). The pathways through which adoption of agricultural technologies may impact poverty are well documented. Direct effects occur through an increase in the welfare of poor farmers who adopt the technological innovation and through the benefits that can ensue from increased production for home consumption, higher gross revenues from sales, and lower production costs from adoption of improved seeds (de Janvry and Sadoulet, 2010). Indirect effects occur when adoption by both poor and non-poor farmers impacts the real income of others through different mechanisms, such as: food prices for consumers; employment and wage effects in agriculture; employment, wages and income effects in other sectors of economic activity (through production, consumption and savings linkages with agriculture); lower costs of agricultural raw materials; lower nominal wages for employers (as a consequence of lower food prices); and foreign exchange contributions of agriculture to overall economic growth (see Adelman, 1975; Haggblade, Hammer and Hazell, 1991).

Notwithstanding the importance of the topic, the literature on the impact of technology adoption on poverty and income in sub-Saharan Africa remains limited and with mixed findings (Verkaart et al., 2017; Cunguara and Darnhofer, 2011; Kassie, Shiferaw and Muricho, 2011), and mostly focusing on hybrid maize in three countries, namely Kenya, Malawi and Zambia (Verkaart et al., 2017).

The paucity of literature can be explained by the fact that establishing causal inference between adoption and poverty outcomes is hindered by data limitations and methodological issues that arise in the absence of randomized experiments. The available studies focus mainly on analysis based on cross-sectional data and non-experimental designs (for example, Mendola, 2007; Becerril and Abdulai, 2010; Asfaw et al., 2012a), although a few studies in a panel-data context exist (for example, Besley and Case, 1993; Suri, 2011; Kassie, Shiferaw and Muricho, 2011; Kikulwe, Kabunga and Qaim, 2012; Mathenge, Smale and Olwande, 2014; Bezu et al., 2014; Verkaart et al., 2017). Data and design limitations were also highlighted in a recent meta-analysis by Stewart et al. (2015), which examines the impact of agricultural technology on livelihoods more broadly. In the absence of randomized experiments where farmers are randomly distributed to two groups (adopters and non-adopters), and where there are no systematic differences across the two, farmers choose to adopt agricultural technologies on a voluntary basis, or they are systematically selected by project implementers or development institutions based on their propensity to participate in the technology adoption decision. This implies that adopters and non-adopters can be systematically different (i.e. due to self-selection or generally selection based on observable or unobservable characteristics). This means that any assessment of the impact of adoption on welfare outcomes with ex-post observational data is challenging.

In this paper, we aim to fill an evidence gap in a number of ways. First, we assess the importance of an adoption determinant that has not been analysed in sufficient detail – path or state dependence. This is defined as the role of farmers' past technology adoption status on contemporary, or current, technology adoption status, on household welfare and on agricultural productivity using a dynamic framework and robust econometric methods. We focus here on the adoption of improved maize seeds because this technology is well known in Uganda.

To our knowledge, path or state dependence has not been sufficiently analysed in the agricultural technology adoption literature, with the exception of the study by Cowan and Gunby (1996), who found that path dependence takes place through learning by using and "learning by doing". Other studies have also examined the importance of learning in adoption of agricultural technologies (e.g. Besley and Case, 1993; Foster and Rosenzweig, 1995; and Suri, 2011). In areas with widespread adoption of a technology, adopters push the technology along the learning curve at a faster speed than in areas with low adoption. Even if farmers face uncertainty regarding the actual benefits of the technology, with greater use, such uncertainty declines as experience accumulates and the incentives to adopt become clearer. Based on these two factors, the value of adopting a technology increases with the degree of adoption.[1] Therefore, our analysis is the first quantitative robust assessment of the importance of state dependence of agricultural technology adoption using robust econometric methods.

Second, this paper assesses the impact of the adoption of improved maize seeds on farmers' welfare and agricultural productivity in a dynamic framework with panel data covering three years. It methodologically addresses the biases noted in the literature, namely, the endogeneity of the adoption decision process, and selection due to both observable and unobservable characteristics. Therefore, we add to knowledge, particularly in the Ugandan context, where the scarce literature on the impact of technology adoption has focused on analyses conducted in a cross-sectional framework (Kassie, Shiferaw and Muricho, 2011; Sserunkuuma, 2005; Tanellari et al., 2014). We estimate the effects on poverty and other welfare indicators by taking into account the decision histories of households' adoption of improved maize seeds, and the various sources of endogeneity.

Third, we relax the learning hypothesis as in Suri (2011) and assess whether returns to adoption on yields and poverty outcomes are heterogeneous across farmers and are conditional on the pattern of adoption of improved maize seeds observed across the various waves of the panel. We find evidence that both learning and experimentation in the form of state dependence play an important role, with past uptake positively influencing current uptake and both yield gains and poverty reduction. However, we also find evidence that while aggregate returns to adoption are positive overall on yields and poverty reduction, there is no heterogeneity regarding yield gains across the different adoption histories. Instead, there is significant

1. Peer effects are also very important in explaining state dependence, as Bandiera and Rasul (2003) and Kasirye (2013) have shown. Oster and Thornton (2012) describe the three ways how these peer effects occur with adoption of any technology. First, farmers may simply want to imitate their peers. Second, farmers may distinguish the positive experience of their peers who adopted a technology. Last, peers may directly share knowledge about this technology with their neighbours and encourage them to adopt it.

heterogeneity in poverty reduction gains, and these are conditional on the adoption history where early adopters switch in and out of the technology to maximize their poverty reduction. The findings hint that farmers seem to have disadopted regardless of the initial gains of the technology to buffer for potential shocks.[2]

Concerning this third aspect, our findings are similar to those in Suri (2011), where individual returns or the comparative advantage were largely negative, but we also add to the literature by stressing that the extent of poverty reduction is indeed correlated with adoption histories. Therefore, policy interventions should possibly target adopters that face liquidity constraints and be tailored to the local context.

This paper is structured as follows. After an analysis of the literature, where we review the empirical evidence, we focus on the identification strategy, presenting the data and the methods, followed by the empirical results. The final section offers recommendations on broad policy concerns.

2. Over the three-year period analysed in this study (2009-2011), unanticipated events impacted the returns of improved maize seeds. A government study estimated that the drought of 2010 led to losses of 7.5 per cent of GDP, equivalent to US$1.2 billion (OPM, 2012). The impact of the drought in the agriculture sector accounted for 77 per cent of the total. Maize was the second-most affected crop, after bananas. In addition, in 2010, the President suspended operations by the National Agricultural Advisory Services for five months due to poor accountability of its funds and to cases of corruption (Kjær and Joughin, 2012). In the context of Uganda, Kijima, Otsuka and Sserunkuuma (2011) examined the dynamics of adoption of NERICA (New Rice for Africa) from 2004 to 2006 and showed how more than 50 per cent of adopting households disadopted two years later because the disseminated improved seeds were not suitable for the local environment in some areas.

2 Literature

It is widely acknowledged that adoption of agricultural technology involves a stepwise process whereby farmers first adopt a new technology on part of their lands and then adjust their use in later years based on what was learned from their partial adoption process. This progression was well documented during the "Green Revolution" era, where farmers initially experimented with the new seed varieties, fertilizer and other new agricultural practices on offer, adopting them only partially at first. Cummings (1975) observed this experimental behaviour of farmers where farmers often adopted in stages, rather than as a complete package. Foster and Rosenzweig (1995) and Munshi (2004) also acknowledged the experimental behaviour of Indian farmers on optimal input use during their adoption of high-yielding varieties in 1968-1970. The study of technology adoption is a complex endeavour and entails a dynamic setting, and needs to be coupled with an examination of the drivers of adoption and an understanding of heterogeneity in both uptake and returns to adoption. Much research has been conducted on the topic. Following the seminal work by Griliches (1957), the early literature on agricultural technology adoption mostly focused on how farmer characteristics and farmland heterogeneity affect adoption decisions in a static set-up. For example, Feder, Just and Zilberman (1985) surveyed the literature on agricultural technology adoption, and suggested that farm size, risk and uncertainty, human capital, labour availability and credit constraints contributed to differences in adoption.

The literature also recognizes the dynamic nature of the adoption process, and it has incorporated the learning component into adoption models (Besley and Case, 1993; Foster and Rosenzweig, 1995; Cowan and Gunby, 1996; Suri, 2011). Both Besley and Case (1993) and Foster and Rosenzweig (1995) modelled farmers' adoption of high-yielding seed varieties with learning in India during the Green Revolution. Comparing models with various assumptions on learning behaviour of farmers, Besley and Case (1993) found that a myopic model, where farmers did not take into account the costs and benefits of adoption in their decision-making process, did not perform well, while the cooperative learning model, in which farmers learned collectively within a village, performed best in predicting the technology diffusion path. Foster and Rosenzweig (1995) explicitly modelled farmers' learning of optimal input usage and compared the effect of self-learning and learning by doing versus learning from neighbours. They found that farmers with more experienced neighbours were more profitable than those without. Both papers confirm that imperfect knowledge of the new technology inhibits adoption and that farmers' learning can significantly reduce uncertainty.

Suri (2011) also reviewed the literature on adoption uptake and surveyed the main drivers of adoption, namely risk management, learning, information, credit availability, taste preferences, agroecology, local costs and benefits, and investment adjustments. She underscored the importance of heterogeneity – where she argued that benefits and costs of technologies are known ex-ante to farmers, but are spatially heterogeneous across them.

She found strong evidence that aggregate returns to hybrid maize in Kenya were positive, while comparative advantage, defined as the individual rate of return, was largely negative and a key element determining yields and adoption decisions. Munshi (2004) also found that the technology adoption impacts were heterogeneous – wheat growers responded strongly to their neighbours' experiences, while rice farmers experimented. Greater variations were found in yields in rice-growing areas, and rice high-yielding varieties, unlike those for wheat, tended to be sensitive to soil characteristics and managerial inputs, which are difficult to observe. Conley and Udry (2010) studied the adoption of fertilizers in the small-scale pineapple industry in Ghana, and collected information on farmers' sources of information. They found evidence of learning, not only from own experiences, but also within information neighbourhoods. Bandiera and Rasul (2003) looked at decisions to plant sunflowers in Zambezia Province in Mozambique. They found that adoption decisions were correlated within networks of family and friends, and that this effect was stronger for disadvantaged farmers. Last, Moser and Barrett (2003) looked at a high-yielding low-external-input rice production method in Madagascar, analysing decisions to adopt, expand and disadopt. They found seasonal liquidity constraints and learning effects from extension agents and other households to be important.

Turning to the specific literature in Uganda and its impact on welfare and agricultural productivity, a number of studies have examined the determinants of adoption in a cross-sectional framework (Kassie, Shiferaw and Muricho, 2011; Sserunkuuma, 2005; Tanellari et al., 2014) and, therefore, cannot shed light on persistence of adoption and disadoption of improved seeds. The first one (Kassie, Shiferaw and Muricho, 2011) used a probit model for the estimation of the probability of groundnut technology adoption coupled with propensity score matching (PSM) techniques and switching regression methods to estimate the effect of groundnut technology adoption on crop income and poverty status of adopters. Positive impacts on crop income and a reduction in the poverty status of adopters were found, with the results robust to presence of selection bias. The second (Sserunkuuma, 2005) presented an analysis of the determinants of improved-seed adoption and land management technology using logit estimations with cross-sectional data in 2000-2001. Land management technologies include inorganic fertilizers, animal manure, incorporation of crop residues and household refuse, mulching, and crop rotation. His analysis showed that adoption of improved seeds was positively influenced by farm size, use of inorganic fertilizer, and freehold tenure system, and negatively by distance to the nearest road. The last study (Tanellari et al., 2014) examined the importance of gender in explaining the adoption of improved seeds on groundnut plots in eastern Uganda with cross-sectional data from 2011. Controlling for exogenous factors and using discrete choice models, the authors found that individual female farmers were less likely to adopt than their male counterparts. The analysis also focused on the intrahousehold decision of adoption of improved groundnut seeds. Results showed that, in male-headed households, female respondents were as likely to adopt as male respondents. However, women in female-headed households were less likely than women in male-headed households to adopt.

Among the research with panel data in Uganda, studies support the finding of positive impacts of improved seeds and extend the analysis to look at the dynamic choice of adoption of improved varieties. Kijima, Otsuka and Sserunkuuma (2011) used a small two-round panel dataset from Uganda in 2004 and 2006 to analyse the probability of uptake of the New Rice for Africa (NERICA) rice variety through a tobit model, combined with a fixed-effect (FE) model to assess its impact on income. Overall, favourable impacts were reported on per capita income and poverty on Ugandan households. However, the authors highlighted that a majority of adopting households in 2004 chose to disadopt two years later due to the low profitability of NERICA.[3]

Using panel survey data in 2000 and 2004, Benin et al. (2011) assessed the impacts of Uganda's National Agricultural Services (NAADS, the main publicly funded agricultural extension institution) activities, on promoting improved seeds, yields, income, assets, perceptions of food security and perceptions of nutrition. Their paper did not examine the determinants of agricultural technology adoption, but found that NAADS' activities led to greater availability of rural public services and services providers. However, enterprise development, yields and agricultural revenue were not greater in areas where NAADS had operations relative to other areas.[4]

Kasirye (2013) used panel data from the nationally representative Living Standard Measurement Surveys (LSMS) for 2005/2006 and 2009/2010 to identify the determinants of improved seeds and fertilizer adoption in Uganda. The results pointed to low education and landholdings as key factors explaining non-adoption. The authors highlighted that peer effects were a key determinant in explaining adoption of these technologies. In addition, greater knowledge in improved seeds, measured with a test enquiring about the respondents' awareness, increased the likelihood of disadoption between 2005/06 and 2009/10. However, the authors did not draw crop-specific conclusions as they chose to focus on the adoption of all types of improved seed varieties.

Even with these studies, which are specific to Uganda, the evidence on the extent to which past experience with agricultural technology affects current adoption decisions, and ultimately their returns, is limited. Therefore, an analysis of state dependence can provide further insights into understanding households' preferences in regard to technology adoption. Specifically, the extent to which positive experience is likely to foster continued adoption of improved seed varieties or any other component or combination, or negative experience lead to disadoption, remains ultimately an empirical question, and one that this paper explores. Therefore, it contributes to the literature in multiple ways, first by looking at state dependence, second by examining the impact of this factor, along with others, on welfare and agricultural outcomes, and last, by looking at whether returns are heterogeneous, conditional on adoption history.

In addition, policy implications can be derived from an analysis of state dependence by examining whether the latter is not only due to households' preferences, but also to contextual factors that characterize specific areas or targeted regions. In essence, an analysis of this kind will allow the role of persistence in the choice of technology adoption to be disentangled from other factors such as the role of extension services. Given the limited empirical literature and the importance of expanding publicly funded projects aimed at diffusing technologies, this empirical analysis is likely to be influential.

3. This improved rice variety had been disseminated in areas with insufficient level of rainfall for NERICA to produce higher yields than traditional crops.

4. In Uganda, about three quarters of agricultural households derive their livelihoods from low-input rainfed agriculture, on holdings of less than 1.5 ha. The agriculture sector accounts for about 15 per cent of GDP and employs about 75 per cent of the total labour force (IFAD, 2013). The government established NAADS in 2001 to implement the national development plan. Its activities included enterprise development and promotion, and the provision of advisory and extension services, targeting the economically active poor to increase access to improved seeds. The outreach of NAADS expanded from 27 subcounties to 545 subcounties in 2007 (83.1 per cent of all Ugandan subcounties). NAADS was a public institution but hired private-sector actors to provide these services to farmers from 2001 to 2008. After 2008, NAADS provided services through public extension agents. It faced difficulties in targeting poorer farmers, women and youth, and in gaining access to high-quality agricultural inputs (Benin et al., 2011). In 2010, the president suspended its operations (see note 2 on p. 8).

3 Data and descriptive statistics

This study employs three waves of panel data, namely the National Panel Survey of Uganda conducted by the Uganda Bureau of Statistics with the support of the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) in 2009/2010, 2010/2011 and 2011/2012.

In the first year, 2009/2010, the nationally representative sample was obtained from the selection of 322 enumeration areas, selected out of 783 enumeration areas covered by the Uganda National Household Survey in 2005/2006. In the raw data, 2,975 households were surveyed in the National Panel Survey of Uganda in 2009. In 2010 and 2011, 2,716 and 2,850 households were interviewed, respectively.

In the household questionnaire, each individual was required to answer questions regarding demographic and socio-economic characteristics (age, sex, marital status, education), health conditions, child nutrition, food and non-food consumption, housing conditions, labour-force status, household income and assets, and financial services, among others. In the community questionnaire, information was elicited on services referring to health, education, social facilities and infrastructure along with information on different community characteristics. Finally, from the agriculture module, it was possible to gather information on land ownership status and soil quality, agricultural and labour inputs used at plot level, crops grown and traditional/improved seeds used, use of fertilizer and pesticides, access to extension services and (proximate) demand for agricultural technology, agricultural production and farm assets in terms of livestock and machinery. This questionnaire was administered twice a year, in order to take into account the two cropping seasons in Uganda.

Merging information from different questionnaires for each year (two seasons in a year for the agriculture modules) allowed us to construct a panel dataset with three periods. We are interested in studying adoption status transition over time. Adopters of new technology are defined as those households that use improved maize seed varieties in the current year (at least once during the two seasons of the year). Hence, technology adoption is a binary variable equal to one in the positive case and zero otherwise.

Table 1 presents observed transition probabilities in the adoption status of improved maize seeds in order to understand preliminary dynamics: on average, the aggregate rate of adoption was 18 per cent in 2009, 11 per cent in 2010, and 13 per cent in 2011. Relative to 2009, there was persistence in their adoption status for about 41 per cent of the sample, while about 5 per cent became adopters. There was also a high persistence in remaining non-adopters (95 per cent), whereas the probability of disadopting was quite high, about 59 per cent from 2009 to 2010. Similar patterns are observed from 2010 to 2011, where 37 per cent remained adopters while 10 per cent became adopters relative to the previous year.

Descriptive statistics about the distribution of households adopting various types of improved seeds are also presented by year (Table 2a). Looking at area planted (in acres) with improved seeds in the sample (Table 2b), we can see how maize is clearly the most commonly used improved seed in terms of both prevalence of adoption and area planted in acres.

Table 1 Descriptive statistics: observed transition probabilities by year, percentage and frequency (in parenthesis)

	Adoption in year 2 (2010)	
Adoption in year 1 (2009)	Non-adopters	Adopters
Non-adopters	95.14 (666)	4.86 (34)
Adopters	58.97 (92)	41.03 (64)
	Adoption in year 3 (2011)	
Adoption in year 2 (2010)	Non-adopters	Adopters
Non-adopters	89.84 (681)	10.16 (77)
Adopters	63.27 (62)	36.73 (113)

Notes:
a. LSMS Uganda, years 2009, 2010 and 2011.
b. Adoption rate in 2009 was 18 per cent, 11 per cent in 2010 and 13 per cent in 2011.
c. Source: authors' calculations.
d. Number of households in each year: 856.

Table 2a Number of households adopting improved seeds by year

	Adoption of ANY improved seeds[1]		**Adoption of MAIZE improved seeds**		**Adoption of BANANA improved seeds**		**Adoption of BEAN improved seeds**		**Adoption of CASSAVA improved seeds**	
	No. households	% of total	No. households	% of no. of households adopting	No. households	% of no. of households adopting	No. households	% of no. of households adopting	No. households	% of no. of households adopting
2009	233	27	156	67	7	3	30	13	42	18
2010	157	18	98	62	5	3	20	13	26	17
2011	224	26	113	50	2	1	31	14	101	45

[1] A household is considered to have adopted a type of improved seed in a specific year if it adopted it in at least one of the two seasons.

Notes:
a. LSMS Uganda, years 2009, 2010 and 2011.
b. Source: authors' calculations.
c. Number of households in each year: 856.

Table 2b Area planted with improved seeds by year

	Total area[1] allocated to agricultural production (acres)[2]	ANY improved seeds		MAIZE improved seeds		BANANA improved seeds		BEAN improved seeds		CASSAVA improved seeds	
		Area (acres)	% of total	Area (acres)	% of area for improved seeds	Area (acres)	% of area for improved seeds	Area (acres)	% of area for improved seeds	Area (acres)	% of area for improved seeds
2009	6,392	354	6	222	63	17	5	32	9	46	13
2010	6,983	205	3	120	59	7	3	20	10	29	14
2011	5,186	310	6	128	41	3	1	31	10	99	32

[1] Areas in this table by year are added across the two seasons.

[2] An acre is about 0.405 hectares.

Notes:
a. LSMS Uganda, years 2009, 2010 and 2011.
b. Source: authors' calculations.
c. Number of households in each year: 856.

Observable characteristics of adopters and non-adopters are presented at baseline in Table 3. Some heterogeneity in household characteristics can be observed where household heads that adopt improved seeds are more likely to be male-headed compared with non-adopter households. The proportion of households with members with no education is lower for adopting households. Access to credit is also lower for adopting households. The asset base and expenditure levels of adopting households are larger than the ones of non-adopting households. There are also differences in agricultural characteristics: the number of crops planted is greater, the land size devoted to maize production of adopters is larger, and the proportion of adopters with flat land is lower compared with the levels observed for non-adopters.

Agroclimatic conditions differ too. Proportions of adopters living in tropic-warm/subhumid conditions are lower, as also in tropic-cool/subhumid conditions, but higher in tropic-cool/humid conditions. Annual precipitation is also higher for adopting households than non-adopting ones.

Turning to agricultural inputs, the use of chemical fertilizer and pesticides seems to be more widespread among adopters – consistent with the hypothesis that adoption of improved maize is coupled with larger use of fertilizer (Suri, 2011) – while use of organic fertilizer does not differ between adopters and non-adopters. A higher proportion of adopting households has also received more advice from NGOs. However, data on "source of agricultural information received" was not available in 2010, and we report and control for only what was observed in 2009 over the whole period.

As far as extension services are considered, adopters have better access to agricultural technology information, with a higher proportion of households receiving agricultural advice. As NAADS constitutes the main source of agricultural advice, the data show that 30 per cent of households were assisted in 2009/2010. Other sources of agricultural advice show very low percentages.

It is important to note that while cross-checking these data with national statistics, despite substantial funding for NAADS, new technology adoption (defined as use of improved seeds, fertilizer and pesticides) remained low and fluctuating. Only 6 per cent of households planted improved seed varieties in 2005/06 (Uganda Bureau of Statistics, 2005), 19 per cent in 2009/10, and barely 10 per cent in 2011/12 (Uganda Bureau of Statistics, 2011).

Table 3 Descriptive statistics – difference in means by adoption status, at baseline (year: 2009)

	Adopters	Non-adopters	P values
Proportion (%)	18.22	81.78	
Sex of household head is female (0=No, 1=Yes)	0.15	0.27	0.00
Age of household head in years	46.04	47.44	0.21
Household members have never received school education (0=No, 1=Yes)	0.43	0.53	0.00
Number of dependants in the household by household size	0.50	0.51	0.43
Household had access to credit in 2009 (0=No, 1=Yes)	0.37	0.45	0.01
Durable and household asset index (predicted with 2009 data)	0.23	0.20	0.00
Distance from community centre to population centre in kilometres	20.63	23.45	0.01
Distance from community centre to major road in kilometres	9.54	8.44	0.09
Distance from community centre to agricultural extension services in kilometres	12.50	14.33	0.00
Number of crops planted by the household	7.93	6.87	0.00
Household adopted chemical fertilizer (0=No, 1=Yes)	0.14	0.05	0.00
Household adopted organic fertilizer (0=No, 1=Yes)	0.21	0.18	0.52
Household adopted pesticides (0=No, 1=Yes)	0.30	0.14	0.00
Tropic-warm/subhumid (0=No, 1=Yes)	0.00	0.04	0.00
Tropic-warm/humid (0=No, 1=Yes)	0.62	0.57	0.37
Tropic-cool/subhumid (0=No, 1=Yes)	0.01	0.12	0.00
Tropic-cool/humid (0=No, 1=Yes)	0.38	0.27	0.00
Total planted area allocated to maize in acres[1]	2.78	1.61	0.00
Share of land with good soil quality	0.38	0.36	0.18
Share of land with fair soil quality	0.20	0.20	0.51
Share of land with poor soil quality	0.05	0.07	0.38
Share of land irrigated	0.02	0.01	0.74
Share of land rainfed	0.60	0.60	0.15
Share of land swamp	0.01	0.01	0.99
Share of land with sand loam	0.27	0.27	0.72
Share of land with sandy clay loam	0.18	0.18	0.84
Share of land with sand black clay	0.09	0.11	0.23
Share of land with other sand	0.08	0.06	0.57
Agricultural advice received from cooperative/farmers association (0=No, 1=Yes)	0.06	0.02	0.00
Agricultural advice received from input supplier (0=No, 1=Yes)	0.04	0.03	0.65

	Adopters	Non-adopters	P values
Agricultural advice received from large-scale farmer (0=No, 1=Yes)	0.03	0.02	0.37
Agricultural advice received from NAADS (0=No, 1=Yes)	0.31	0.30	0.08
Agricultural advice received from NGO (0=No, 1=Yes)	0.08	0.06	0.00
Household experienced drought/irregular rains (0=No, 1=Yes)	0.51	0.61	0.97
Parcel is flat (0=No, 1=Yes)	0.03	0.12	0.00
Slope of parcel is gentle (0=No, 1=Yes)	0.54	0.58	0.24
Parcel is hilly (0=No, 1=Yes)	0.59	0.48	0.01
Annual precipitation in the community in millimetres	1 327.71	1 239.89	0.00
Daily constant total expenditure in US$ PPP per adult equivalent	2.83	2.23	0.00
Daily constant non-food expenditure in US$ PPP per adult equivalent	1.52	1.26	0.01
Daily constant food expenditure in US$ PPP per adult equivalent	1.31	0.98	0.00
Household lives in Central Region (0=No, 1=Yes)	0.19	0.20	0.47
Household lives in Eastern Region (0=No, 1=Yes)	0.51	0.23	0.00
Household lives in Northern Region (0=No, 1=Yes)	0.28	0.32	0.24
Household lives in Western Region (0=No, 1=Yes)	0.02	0.24	0.00

[1]An acre is about 0.405 hectares.

Notes:

a. LSMS Uganda, year 2009.

b. Source: authors' estimations.

c. Number of observations: 856.

4 Modelling adoption of improved maize seeds: estimation strategy

First-stage estimation framework

The adoption of improved maize seeds and the impact thereof on agricultural productivity and welfare are modelled in a two-stage framework.

In the first stage, we present a selection model for the contemporary or current decision to adopt improved maize seeds where risk-averse farmers choose to adopt if the technology maximizes their expected utility.

The probability of technology adoption at time t is therefore defined as a dummy variable y_{it}=1 if households adopt improved seed varieties and y_{it}=0 otherwise. Households maximize their utility (Equation 1) and choose to adopt agricultural technology if their utility derived by adopting technology, $U_{i,1t}$, is greater than zero:

If $U_{i,1t} > 0$, then $y_{it} = 1$.
If $U_{i,0t} \leq 0$, then $y_{it} = 0$.

With:

$$U_{i,1t} = \beta X_{it} + \gamma Z_i + \rho y_{it-1} + \varepsilon_{it} + c_i \qquad (1)$$

where X is a matrix of time-variant characteristics of household i at time t; Z is a matrix of time-invariant characteristics of household i; y_{it-1} is the adoption status in the previous year and if $\rho > 0$ there is positive state dependence; ε_{it} is the error term; and c_i is the individual unobserved time-invariant heterogeneity.

Direct net utility is not observed (Equation 1), but we can observe the technology adoption decision, assumed to be the result of a utility maximization problem. Hence, the probability of technology adoption is modelled in the following way (Equation 2), where the probability of adoption is a function of previous adoption (or lagged adoption), initial adoption and other covariates:

$$Pr(y_{it} = 1 | X_{it}, Z_i, y_{it-1}, c_i) = Pr(U_{i,1t} > 0) = \Phi(\beta X_{it} + \gamma Z_i + \rho y_{it-1} + \mu y_0 + \varepsilon_{it} + c_i) \qquad (2)$$

where $\Phi(.)$ is the standard normal distribution function, assuming that ε_{it} is normally distributed with mean equal to zero and variance equal to σ_ε^2. Note that this is a model that is autoregressive of order 1 (AR[1]).

In this dynamic setting, there are two potential sources of bias: (i) unobserved time constant heterogeneity c_i (where bias arises if c_i and the covariates are correlated, which occurs when the assumption of strictly exogenous explanatory variables does not hold); and (ii) the correlation between c_i and the lagged adoption decision y_{it-1} (Wooldridge, 2005).

We control for unobserved heterogeneity c_i by using a framework called either correlated random effects (CRE) or the Mundlak–Chamberlain approach, following Mundlak (1978) and Chamberlain (1984). To implement the CRE framework in Equation 2, we include a vector of variables containing the means for household i of all time-varying covariates,[5] denoted by $\bar{X}_i$. These variables have the same value for each household in every year but vary across households. One benefit of the CRE estimator is that by including the vector of time-averaged variables, we control for time-constant unobserved heterogeneity as with fixed-effects while avoiding the problem of incidental parameters (Mundlak, 1978) that occurs in non-linear models. Another advantage of CRE is that it allows measurement of the effects of time-constant independent variables as in the standard traditional random-effects estimator framework (Wooldridge, 2010).

Second, the "initial condition problem" could be instead ruled out by assuming that c_i and y_{i0} are uncorrelated, where y_{i0} is the initial technology adoption decision. However, this is a very restrictive assumption (Wooldridge, 2005), and it is not likely to hold in our case because the first period of technology adoption (first year: 2009) in our data does not coincide with the true start of the technology adoption process. In Uganda, improved seed varieties have been diffused since the early 2000s (Benin et al., 2011).

Wooldridge (2005) proposes a solution for this issue in dynamic non-linear panel data models with unobserved heterogeneity, whereby c_i; the unobserved heterogeneity is given by Equation 3:

$$c_i = \lambda + \eta\bar{X}_i + \mu y_{i0} + \alpha_i \tag{3}$$

as a function of y_{i0}. Here, α_i is assumed to be normally distributed with mean equal to zero and variance equal to σ_α^2 and uncorrelated with $\bar{X}_i$ and y_{i0}.

The parameters of interest are estimated by substituting Equation 3 in the following Equation 4:

$$Pr(y_{it} = 1|X_{it}, Z_i, y_{it-1}, c_i) = \Phi(\beta X_{it} + \gamma Z_i + \rho y_{it-1} + \varepsilon_{it} + \lambda + \eta\bar{X}_i + \mu y_{i0} + \alpha_i) \tag{4}$$

and, relying on the highlighted assumptions presented in the Wooldridge (2005) approach, by implementing a probit model to estimate the selection equation.

Second-stage estimation framework

In the second stage, the following structural model of interest is estimated:

$$W_{it} = \delta + \alpha y_{it} + \beta X_{it} + \gamma Z_i + \partial \boldsymbol{t} + \eta_{it} \tag{5}$$

$$\eta_{it} = \epsilon_i + \nu_{it}$$

5. We include the mean of the following time-varying variables: household members have never received school education (0=No, 1=Yes); distance from community centre to agricultural extension services in kilometres; share of land rainfed; share of land with sand loam; share of land with good soil quality; and household experienced drought/irregular rains (0=No, 1=Yes). The mean of other variables, which were considered time-variant (such as the number of dependants in the households by the total number of household members), were included but it led to perfect multicollinearity. Thus, they were removed.

where W_{it} is a vector of outcome variables (either consumption expenditure, poverty proxies and agricultural outcomes, which include total value of agricultural production, total yields, value of production from improved maize seeds, and yields from improved maize seeds); y_{it} is contemporary technology adoption (current adoption of improved maize seeds), which is endogenous. X_{it} is a vector of time-varying exogenous variables, Z_i is a vector of time-invariant exogenous variables.

Note that here η_{it} represents a compound error that include time-constant ϵ_i and time-varying unobserved heterogeneity v_{it}.

A third econometric issue may plague the structural model of interest, namely η_{it}, the unobserved time-varying heterogeneity, which could be thought of as a vector of time-varying shocks affecting the contemporary or current adoption decision. This shock could be embodied by the differential access of improved maize seeds, which can occur when seed dissemination and extension activities are targeted to specific villages and farmers (Asfaw et al., 2012a; Shiferaw et al., 2014). This essentially implies selection, for example, that access to technology is dynamic and non-random, and likely to be correlated with time-varying characteristics. In other words, there could be a selection conditional on both time-varying observables and unobservables that could bias the parameter estimates.

A possible way to factor in unobserved time-varying heterogeneity, or more precisely endogeneity due also to selection, in other words when the contemporary adoption decision is correlated with η_{it}, is through the use of a control function approach (Lewbel, 2007; Papke and Wooldridge, 2008; Rivers and Vuong, 1988; Smith and Blundell, 1986; Vella, 1993). This essentially means that we take the generalized residuals from the first-stage estimation and include them as a covariate in the structural models of interest.

The structural models of interest are therefore estimated through a number of estimators, conditional on relaxing the assumptions of strict exogeneity and unobserved heterogeneity, and contingent on the dependent variable under analysis. These models have been widely used in the adoption literature; therefore, we take an agnostic stance and compare their performance conditional on the econometric assumptions being made.

Based on the relevant literature on the topic, we assess the robustness of our approach by comparing results across: (i) standard panel data estimators; (ii) PSM estimators; (iii) Heckman selection estimator; (iv) endogenous switching regression model (ESRM); (v) a control function approach (CF) combined with CRE for binary poverty outcomes (namely, the poverty headcount) and FE, which are instead suitable for continuous poverty outcomes and agricultural outcomes; and (vi) a CF approach combined with both CRE and double-hurdle model (DH) for variables that present a non-linear corner solution, namely, improved maize yields in kilograms and value of production from improved maize seeds (in constant Ugandan Shillings), as in Verkaart et al. (2017). These two outcomes can only be observed for adopters, while they take a value of zero for non-adopters or are simply not observed. Last, we run a correlated random coefficient model (CRC), as in Suri (2011), to further explore whether returns to adoption are correlated with the individual choice to adopt and are therefore heterogenous.[6]

6. For models 1, 2, 3, 4, 5 and 7, we exclude households with no agricultural production to avoid a corner solution situation. In model 6 (a CF approach combined with both CRE and DH model), these households are included.

In essence, our methodological approach is sequential in dealing with econometric rigour instrumental to understanding the adoption decision process. After dealing with the potential endogeneity of the lagged adoption decision process in the first stage and unobserved heterogeneity, we consider the possibility of fitting a DH – primarily to deal with corner solutions variables; last, we conclude with a CRC to explore the potential heterogeneity in returns to improved maize seed adoption and whether the latter is correlated with the adoption decision history. We explain the models and their underlying assumptions, in turn, below.

Panel data estimators

Standard panel data estimators are presented first where random effects assume that the unobserved heterogeneity is treated as random and uncorrelated with the independent variables and fixed effects models assume that unobserved heterogeneity is treated as fixed and constant over time. The results of the standard fixed effects and random effects estimators are presented in Tables 6 and 7 (the full estimations are available upon request).

Propensity score matching

A number of papers in the technology adoption literature (Khonje et al., 2015; Shiferaw et al., 2014) resort to the use of propensity score matching to account for selection on observables. The conditional independence assumption holds also here as in the ordinary least squares framework, indicating that the decision to adopt is independent given the covariates. However, this approach might yield biased estimates because it assumes that adoption of improved seeds is exogenously determined while it is potentially endogenous. The decision to adopt improved maize seeds is voluntary and may be based on individual self-selection. Farmers that adopted may have systematically different characteristics from the farmers that did not adopt, and they may have decided to adopt based on their expected utility or other factors. Unobservable farmers and farm characteristics may affect both the adoption decision and their yields as well as their returns, resulting in inconsistent estimates of the effect of adoption on agricultural productivity. For example, if only the most capable or motivated farmers choose to adopt, and we fail to control for ability (skills), then we may incur an upward bias.

Therefore, the assumption here is that adopting and non-adopting households are only different conditional on observable characteristics and are therefore matched with PSM across the two main outcomes (poverty and agricultural outcomes). Households are matched at baseline (2009) based on a number of covariates measured in 2009 and assumed not to influence the forward adoption decision process. For the different outcomes, the estimation samples are different and the analysis sample is restricted to those observations that are within the common support region. The common support is also trimmed at the lowest and highest 2 per cent of the propensity score.[7] For each household, the propensity score of adopting agricultural technology is estimated using the nearest neighbour matching algorithm with five neighbours.

The average treatment effect on the treated (ATT) is estimated as in Equation 6 (i.e. the difference between the outcome variable for the adopting households and the outcome variable for the non-adopting households had they adopted). The latter quantity is unobserved. Equation 6 illustrates the relationship:

7. This ensures that matched observations with very low and very high propensity scores of adopting are not included in the analysis. These observations could be considered outliers.

$$ATT = E[E\{w_{1t} - w_{0t}/y_{it} = 1, p(X_{it})\}] \quad (6)$$

where:

ATT: average treatment effect on the treated.

w_{1t}: outcome variable for adopting households (consumption expenditure, poverty proxies, and total agricultural outcomes).

w_{0t}: outcome variable for non-adopting households had they adopted.

X_{it}: is a vector of characteristics including whether sex of household head is female (0=No, 1=Yes), the number of dependants in the household by household size, the household members have never received school education (0=No, 1=Yes), the climate is tropic-cool/humid (0=No, 1=Yes), the household experienced drought/irregular rains (0=No, 1=Yes), source of agricultural advice received by household (1=none 2=other sources 3=NAADS, none is the reference category), the share of land with good soil quality, and the seed was bought in local/village market (0=No, 1=Yes).

y_{it}: contemporary technology adoption (adoption of improved maize seeds).

$p(X_{it})$: propensity score based on the exogenous variables measured at baseline (X_{it}).

The distribution of the propensity score of adopting improved maize seeds for the adopting households and non-adopting households and the Rosenbaum and Rubin's bias graph are available upon request.

Heckman selection model

Selection on observables might not be the only possibility in this empirical framework. Therefore, we turn to a suite of models that allow for the possibility of selection on unobservables. In the technology adoption literature, a number of studies (Lambrecht et al., 2014; Kassie et al., 2013) have resorted to Heckman selection models to understand and control for non-exposure bias, selection bias, and possible endogeneity bias of the adoption decision process. The Heckman selection model can thus control for both observed and unobserved heterogeneity, and clustering of errors at the community level.

Note that for this framework, an instrumental variable is required. In our paper, the selection of instrumental variables (IVs) follows the strategy of other studies (e.g. Asfaw et al., 2012b; Bezu et al., 2014; Mathenge, Smale and Olwande, 2014; Shiferaw et al., 2014; Smale and Mason, 2014) where variables relating to access to information, access to inputs, influence of the household in the local community, and the level of adoption in the local community or district were all considered and tested as possible instruments in the estimation of the impact of technology adoption on welfare and agricultural outcomes. The acceptability of instruments is established by conducting a simple rejection test following the approach presented in Di Falco, Veronesi and Yesuf (2011): if a variable is a valid instrument, it will affect the technology adoption decision but it will not affect the outcome variables among the households that did not adopt agricultural technology. This rejection test represents the best way to test for the suitability of IVs according to the literature with similar research questions and estimation frameworks (Asfaw et al., 2012b; Shiferaw et al., 2014; Smale and Mason, 2014).[8]

8. The instrument is defined as the ratio of number of adopting households over the total number of households in the community. A separate estimation sample is employed for each outcome (poverty, and agricultural outcomes) contingent on the number of observations. We test for the validity of the selected IVs in each estimation sample.

As suitable instruments, we chose two instruments: the proportion of households adopting improved maize seeds in the community; and the log of the distance from the community centre to agricultural extension services. The hypothesis made here is that, in an area with a high proportion of adopters, an individual household is more likely to adopt as the information about the technology is shared and discussed frequently in the neighbourhood. This variable is not directly correlated with the outcome variables of interest or with the unobserved errors in the second stage.[9]

Following the rejection test suggested by Di Falco, Veronesi and Yesuf (2011), Table 4 shows the results and indicates that the instruments affect the adoption decision of improved maize seeds in both estimation samples (p values are 0.00 for both analysed outcomes in Table 4). We find similar results with the standard panel-data IV model test.[10]

Table 4 Instrumental-variable tests

Poverty dataset

Instrumental variables (IVs):

- Proportion of households adopting improved maize seeds in the community (varies by year)
- Log of distance from community centre to agricultural extension services in kilometres

Outcome variable: Log of daily constant food expenditure in US$ PPP per adult equivalent. The results below are similar for the other poverty outcomes.

	Di Falco, Veronesi and Yesuf (2011) tests	Panel-data IV model tests
Joint relevance test	$chi^2(2) = 763.92$ p value = 0.0000	F(2,1555) = 317.66 p value = 0.0000
Joint exclusion restriction test	$chi^2(2) = 2.93$ p value = 0.2306	Sargan statistic: p value = 0.8749

Agricultural dataset

IVs used:

- Proportion of households adopting improved maize seeds in the community (varies by year)
- Log of distance from community centre to agricultural extension services in kilometres

Outcome variable: Log of total agricultural yields in kilograms.
The results below are similar for the other agricultural outcomes.

	Di Falco, Veronesi and Yesuf (2011) tests	Panel-data IV model tests
Joint relevance test (first)	$chi^2(2) = 507.17$ p value = 0.0000	F(2,835) = 182.87 p value = 0.0000
Joint exclusion restriction test	$chi^2(2) = 0.50$ p value = 0.7807	Sargan statistic: p value = 0.8413

Notes:
a. Clustered standard errors in parentheses, * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.
b. LSMS Uganda, years 2009, 2010 and 2011.
c. Source: authors' estimations.

9. Exogenous community-level variables controlling for community local economic development are included as covariates in the model as described in section 4.2. These include: agroclimatic conditions, annual precipitation in the community, distance from community centre to agricultural extension services, distance to population centre and distance to a major road.
10. The same covariates employed in the estimation of the first-stage regression are employed to estimate the factors explaining adoption of improved maize seeds (as in the Mundlak-Wooldridge model), to which we add the selected IVs in this first-stage estimation to identify whether they affect the adoption dummy (the Heckman selection equation).

Table 4 also shows the results and illustrates that the selected IVs do not affect the welfare and agricultural outcome variables among the households that did not adopt improved maize seeds (for the log of total value from agricultural production in Ugandan shillings, the p value from the Di Falco, Veronesi and Yesuf (2011) test is 0.78, and the p value from the Sargan statistic is 0.84). From Table 4, we can thus infer that the selected IVs fulfil the exclusion restrictions across these estimations as they affect the technology adoption decision but are not correlated with the outcome variables for households that did not adopt agricultural technology.

In the Heckman selection model, selection bias is addressed first by estimating the first-stage model (Equation 4) and by adding the inverse Mills ratio in the second-stage model (Heckman, 1979). Errors in both stages are assumed to be bivariate normally distributed. Error terms estimated in both stages are also assumed to be independent of observable data. A two-step Heckman selection model is employed to estimate treatment effects.

The first stage is identical to the one presented in Section 5.1. In the second stage, for continuous outcome variables (namely the poverty variables), the second-stage model is estimated by including the inverse Mills ratio as a covariate in the following model:

$$w_{it} = \delta + \pi\lambda_{it} + \beta X_{it} + \partial t + \eta_{it} \tag{7}$$

where:

λ_{it}: inverse Mills ratio calculated from the first-stage equation (see Equation 4).

t: time variable (dummies indicating the year).

X_{it}: exogenous variables (sex, age and ethnicity of household head, the number of dependants in the households by the total number of household members, the number of years the household has lived in this district, the share of land rainfed, the share of land with sandy loam, the share of land with good soil quality, a vector of variables indicating distance to population centre, distance from village centre to agricultural extension centre, distance to a major road, asset index, annual precipitation in the community in millimetres, source of agricultural advice received by household [1=none, 2=other sources, 3=NAADS, none is the reference category], binary variables indicating whether the household members received any school education [0=No, 1=Yes], parcel is flat [0=No, 1=Yes], slope of parcel is gentle [0=No, 1=Yes], the occurrence of irregular rains [0=No, 1=Yes], the household is located in a tropic-cool/humid area [0=No, 1=Yes], household had access to credit in 2009 [0=No, 1=Yes], seed was bought in local/village market [0=No, 1=Yes], and dummy variables for years and regions).

As for the first stage, the mean of time-variant variables, the lagged adoption of improved maize seeds (0=No, 1=Yes), and the initial adoption of improved maize seeds (0=No, 1=Yes) are also included. Standard errors are clustered at the community level.

For binary outcomes, while the specification for the first stage is identical, the second stage employs a probit estimation model (Equation 8):[11]

$$Pr(w_{it} = 1 | X_{it}, Z_i, c_i, \lambda_{it}) = \Phi(\beta X_{it} + \partial t + \pi\lambda_{it} + \eta_{it}) \tag{8}$$

11. The routine "heckprobit" is employed in STATA 14 to fit the two-step Heckman selection model in a potential outcome model for binary outcomes.

The ATTs of agricultural technology are therefore estimated while accounting for selection bias due to unobservable selection. We choose to use a two-stage model (where we manually estimate the selection equation using a probit model for sample inclusion with random effects, as described in the first stage, followed by a panel data regression with the estimated inverse Mills ratio). Other selection models (ivtreatreg and heckprobit in STATA 14) are more efficient, but they fail to exploit the panel nature of the data and instead pool the data across the three years. We report estimates in Tables 6 and 7 (the full estimations are available upon request).

Endogenous switching regression model (ESRM)

As in the Heckman selection model, the decision to adopt agricultural technology can be modelled in two stages. Once again, in the technology adoption literature, many papers (e.g. Asfaw et al., 2012a; Asfaw et al., 2012b; Shiferaw et al., 2014) argue that the ESRM approach is superior. PSM only controls for observed heterogeneity, and IV can also control for unobserved heterogeneity. The traditional IV treatment effect models with one selection and outcome equation assume that the impact can be represented as a simple parallel shift with respect to the outcome variable. The ESRM framework relaxes this assumption by estimating two separate equations – one for adopters (Equation 9), and one for non-adopters (Equation 10).

The full-information maximum likelihood method is employed to estimate both a binary (first-stage) and a continuous (second-stage) outcome variable. The first stage is again the one presented in Section 5.1. In the second stage, this estimation strategy uses the same IVs and addresses the potential selection bias as in the Heckman selection model. This methodology provides consistent standard errors.

For adopting households (regime 1):

$$w_{1it} = \delta + \beta_1 X_{1it} + \partial t + \eta_{1it} \quad if\ y_{it} = 1 \tag{9}$$

For non-adopting households (regime 2):

$$w_{2it} = \delta + \beta_2 X_{2it} + \partial t + \eta_{2it} \quad if\ y_{it} = 0 \tag{10}$$

where:

β: is the vector of parameters to be estimated.

t: time variable (dummies indicating the year).

X_{it}: the covariates are the same as the ones presented in the Heckman selection model. Standard errors are clustered at the community level.

η_{1it}: error term in Equation 9.

η_{2it}: error term in Equation 10.

Errors in the first stage and in Equations 9 and 10 are assumed to have a trivariate normal distribution with mean zero and a covariance matrix as specified in Equation 11:

$$cov(\varepsilon_{1it}, \eta_{1it}, \eta_{2it}) = \begin{matrix} \sigma_{\varepsilon}^{2} & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{1\varepsilon} & \sigma_{1}^{2} & . \\ \sigma_{2\varepsilon} & . & \sigma_{2}^{2} \end{matrix} \qquad (11)$$

where:

σ_{ε}^{2} is the variance of ε_{1it}.

σ_{1}^{2} is the variance of η_{1it}.

σ_{2}^{2} is the variance of η_{2it}.

$\sigma_{1\varepsilon}$ is the covariance of ε_{1it} and η_{1it}.

$\sigma_{2\varepsilon}$ is the covariance of ε_{1it} and η_{2it}.

σ_{ε}^{2} is assumed to be equal to 1.

The covariance between ε_{1it} and ε_{2it} is not defined as w_{1it} and w_{2it} are not observed simultaneously. The expected values of ε_{1it} and ε_{2it} conditional on the sample selection is non-zero because the error term in the first stage is correlated with the error terms of the second stage, see Equations 12 and 13.

$$E(\eta_{i1} | y_{it} = 1) = \sigma_{1\varepsilon} \lambda_{i1t} \qquad (12)$$

$$E(\eta_{i2} | y_{it} = 0) = \sigma_{2\varepsilon} \lambda_{i2t} \qquad (13)$$

The inverse Mills ratios (λ_{1it} and λ_{2it}) computed from the first stage are included in the second-stage Equations 9 and 10 to account for selection bias in a two-step estimation framework.

Adopters with adoption (observed in the sample):

$$E(w_{1it} | y_{it} = 1, X) = \beta_1 X_{1it} + \sigma_{1\varepsilon\varepsilon} \lambda_{1it} \qquad (14)$$

Non-adopters without adoption (observed in the sample):

$$E(w_{2it} | y_{it} = 0, X) = \beta_2 X_{2it} + \sigma_{2\varepsilon\varepsilon} \lambda_{2it} \qquad (15)$$

Non-adopters had they decided to adopt (counterfactual):

$$E(w_{1it} | y_{it} = 0, X) = \beta_1 X_{2it} + \sigma_{1\varepsilon\varepsilon} \lambda_{2it} \qquad (16)$$

Adopters had they decided not to adopt (counterfactual):

$$E(w_{2it} | y_{it} = 1, X) = \beta_2 X_{1it} + \sigma_{2\varepsilon\varepsilon} \lambda_{1it} \qquad (17)$$

From Equations 14 to 17, ATT and the average treatment effect on the untreated (ATU) can be calculated. ATT represents the expected change in adopters' mean outcome if adopters' characteristics had the same return of the ones of non-adopters or if adopters had similar characteristics as non-adopters (Equations 18 and 19). ATU is the expected change in non-adopters mean outcome if non-adopters' characteristics had the same return as adopters or if non-adopters had similar characteristics as adopters (Equations 20 and 21).

$$ATT = E(w_{1it} \mid y_{it} = 1, X) - E(w_{2it} \mid y_{it} = 1, X) \tag{18}$$

$$ATT = X_{1it}(\beta_1 - \beta_2) + \lambda_{1it}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \tag{19}$$

$$ATU = E(w_{1it} \mid y_{it} = 0, X) - E(w_{2it} \mid y_{it} = 0, X) \tag{20}$$

$$ATU = X_{2it}(\beta_1 - \beta_2) + \lambda_{2it}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \tag{21}$$

The first term in Equation 19 represents the expected change in adopters' mean outcome variable if adopters had similar characteristics as non-adopters. The second term is the selection term that captures the differences in unobserved characteristics. Similarly, for Equation 21, the first term shows the expected change in outcome variables of non-adopters if non-adopters had similar characteristics as adopters. Equally, the second term is the selection term that captures all potential effects due to differences in unobserved variables. For the binary variables, the second stage is fitted with a linear probability model. We report estimates in Table 8, with the full estimations presented in Section 5.2 (Tables 9-12).

Control-function approaches allowing for both time-varying and time-constant unobserved heterogeneity

We now turn to a CF combined with CRE for binary poverty outcomes (namely, the poverty headcount) and fixed effects or two stages within estimator, with IVs (for continuous poverty outcomes and agricultural outcomes) to take into account the various sources of endogeneity discussed above. While in linear models, the CF leads to the two-stage least squares estimators, in non-linear models these two approaches will give different results (Imbens and Wooldridge, 2008; Lewbel, 2007). In these cases, the CF is more efficient than the two-stage least squares. The methodology essentially involves estimating a reduced-form probit model that predicts adoption of improved seeds.

The CF requires an IV to be used in the reduced form model (selection equation) that is not used in the structural model. As IVs, we choose the proportion of households adopting improved maize seeds in the community and the log of distance from community centre to agricultural extension services in kilometres. Tables 6, 7 and Appendix A2.1 display the results of this model (the full estimations are available upon request).

Control-function approaches allowing for both time-varying and time-constant unobserved heterogeneity for variables that present a non-linear corner solution

We apply a CF combined with CRE and DH for variables that present a non-linear corner solution, namely, improved maize yields in kilograms and value of production from improved maize seeds (in constant Ugandan Shillings). In order to look at the improved maize seeds equation, we resort to such models, as some authors (Verkaart et al., 2017) have argued that the improved maize seed equation is best formulated in the framework of a corner solution model. These models acknowledge that the optimal choice for some of the agents facing various constraints is at zero (Wooldridge, 2010). So, for example, A_{it}, the vector of improved maize outcomes, is given by the following in Equation 22:

$$A_{it} = max\ (0, A_{it}^{*}) \tag{22}$$

where A_{it}^{*} refers to a linear specification of the improved maize seed adoption equation.

In essence, our methodological approach is sequential in dealing with econometric rigour instrumental to understanding the adoption decision process. After dealing with the potential endogeneity of the lagged adoption decision process in the first stage and unobserved heterogeneity, we now consider the possibility of fitting a DH – primarily to deal with corner solutions variables. In other words, a Heckman selection approach would be appropriate in this context because a portion of households do not use improved maize seeds (58.55 per cent of the households in the sample). However, the Heckman approach is designed for incidental truncation where the zeros are unobserved values, such as in the case of wage rate models where the sample does not include unemployed persons. In this paper, with the Heckman selection model, we first exclude the households with no maize production in any one year of the panel data when examining the effect of improved maize seeds on total agricultural production. A corner solution model is more appropriate than a selection model for the analysis of production using improved maize seed when household prevalence of non-adoption of improved maize seeds is high, resulting in a censored dependent variable. This is because improved maize seeds are available on the market, so we could assume that farmers are aware of them, implying that farmers make a conscious choice of non-adopting. For corner solution variables, the literature has suggested either the tobit estimator, or Cragg's DH estimator (Cragg, 1971) – with the latter deemed more flexible given the possibility of including different variables in both the reduced form and the structural form. The latter is a two-tier truncated normal hurdle model, which extends the standard tobit model by assuming that the adoption decision follows a probit model, while the amount of intensity decision has a truncated normal distribution. Therefore, adoption and intensity are supposed to be independent in this model. We combine both the CF and the Cragg's DH to take into account unobserved heterogeneity and the distribution of the outcome variable. We report estimates in Table 14 (DH), with full estimations given in Section 5.2 (Tables 15 and 16).

Correlated random coefficient model

Last, we present the Suri (2011) correlated random coefficient model (CRC) to explore the potential heterogeneity in returns to adoption of improved maize seeds and whether the latter is correlated with adoption decision histories.

The contribution of Suri (2011) in the development literature highlights how the household FE framework is restrictive in the assumptions it imposes on the adoption process and the comparison of adopters and non-adopters. In fact, it assumes that there is no difference between farmers who adopt an improved variety and those who disadopt the improved variety. The different agroeconomic and economic factors, which include barriers to adoption, notably, the inappropriate diffusion of information (extension information asymmetries) and credit constraints, imply that the distribution of returns to the technology is heterogeneous and conditional on observable and unobservable factors. Therefore, selection and heterogeneous returns are essential elements of the adoption decision process.

This estimation strategy is a generalization of the Chamberlain (1982, 1984) CRE, and it parallels Chamberlain in how the model is identified. While CRE uses a linear projection onto the history of adoption decisions on improved maize seeds, CRC allows us to project also onto their interactions. The reduced-form model (Suri, 2011) essentially gives two additional parameters of interest, relative to Chamberlain (1984), notably β and φ, where β is the aggregate return to yields, which is independent of the technology used, and φ is a coefficient that describes how important differences in individual returns to adoption or comparative advantage are in this context. In addition, there is another parameter of interest, θ, which depends on φ and measures farmers' relative productivity with improved maize seeds relative to unimproved maize seeds, namely, their comparative advantage in adopting this technology. If farmers with a high θ have lower gains from moving from adopting to disadopting, then φ is negative. In that case, relative to the mean θ in the population, a farmer would need a small θ to meet the adoption criterion. This is what Suri (2011) describes as the notion of selection on the basis of comparative advantage, in that those with lower baseline productivity have larger gains from switching to the new technology. Therefore, the coefficient φ describes the sorting in the economy. If φ is negative, there is less inequality in yields in this economy compared with an economy where individuals are randomly allocated to a technology. On the other hand, if φ is positive, then the self-selection process leads to greater inequality in yields. We report results in Appendix 1.

5 Results

First-stage[12] estimation: results

Table 5 presents the average partial effects from the CRE model. State dependence is statistically significant and indicates that the decision to adopt in the previous period strongly affects current choice, by 17 per cent. We also control for initial conditions, namely the technology adoption decision in 2009, and also find that the latter significantly influences current technology adoption decisions (by 11 per cent).

Looking at other determinants, we find that the probability of technology adoption increases if the household head is male, while variables related to land and parcel size and education of both the head and other members in the household do not exhibit any significant impacts. Having a sloped parcel reduces the probability of adopting.

Distance from village centre to market and household distance to a major road have no major effect on adoption. Although distance from village centre to agricultural extension services might be the only relevant factor that could facilitate adoption, the coefficient is also not significant. Despite the use of GPS data, these results might be due to measurement error. Alternatively, these variables might not be truly important in explaining agricultural technology adoption.

12. In the first stage, we distinguish the determinants of adoption of improved maize seeds with 856 households in each year (2,568 observations over the three years). The dataset is characterized by an attrition rate of 52 per cent from 2009 to 2011. In the baseline year, the total number of households in the analysed data is 1,300; in the second and the third waves, the number of households is 1,187 and 1,075, respectively.

    In the second stage, the dataset is used for the analysis of the impact of improved maize seeds on consumption expenditure and poverty outcome variables. We remove here households that do not grow maize in any of the years (2009, 2010 and 2011), which corresponds to 207 observations (or 69 households). The dataset contains 787 households in each year (2,361 observations over the three years). In the second stage, we also assess the impact of these improved seeds on agricultural variables (notably yields and value of agricultural production). In this way, we drop observations for years when households in the sample are not growing maize. We also balance the dataset here, and 427 households in each year remain (1,281 observations over the three years), for an attrition rate of 52 per cent.

    When we difference the mean of these variables across the balanced panel observations with the attrited observations, we find that a large majority of variables are balanced, indicating that the attrition bias is unlikely to affect results (this table is not shown in this paper, but available upon request). Not balanced are: the number of dependants in the households by the total number of household members, tropic-warm/humid (0=No, 1=Yes), the distance from community centre to agricultural extension services in kilometres, the number of crops planted by the household, the share of land rainfed, agricultural advice received from NAADS (0=No, 1=Yes), the household experienced drought/irregular rains (0=No, 1=Yes), the parcel is flat (0=No, 1=Yes), the household lives in Northern Region (0=No, 1=Yes), and the household lives in Western Region (0=No, 1=Yes). We obtain the same results for the dataset used for the impact of improved maize seeds on agricultural outcomes (also available upon request).

We also find that geographic characteristics are also important, and that regions characterized by tropic-cool/subhumid agroecological zones are negatively associated with the adoption of new technology. In terms of regional characteristics, residence in the Northern Region significantly influence the probability of adoption.

Two variables exhibit a positive and significant coefficient, namely, accessibility of seed in the local village market and whether the households received agricultural advice from NAADS in 2009 (2 and 3 per cent, respectively). We have this last variable only in the 2009 data. These variables hint at existing constraints to adoption diffusion.

There is a strong and negative time trend, with the years 2010 and 2011 both having a negative impact on adoption relative to 2009. This could capture the presence of unobserved shocks, although two factors may have driven this negative time trend, namely, the dramatic drought that occurred during 2010 as well as a sharp cutback in NAADS' expenditure in 2010/11, which may have influenced seed distribution and/or the extent of extension advice. However, in controlling for households experiencing drought, the latter is not significant and the coefficient is negative. Thus, something might have prompted households to disadopt in subsequent years, and we investigate this in the remainder of the paper.

Table 5 Average partial effects of factors explaining current (contemporary) adoption of improved maize seeds

	Mundlak-Wooldridge model
Lagged adoption of improved maize seeds (0=No, 1=Yes)	0.17*** (0.01)
Initial adoption of improved maize seeds (0=No, 1=Yes)	0.11*** (0.01)
Durable and household asset index (predicted with 2009 data)	0.02 (0.04)
Sex of household head is female (0=No, 1=Yes)	-0.02* (0.01)
Age of household head in years	0.00 (0.00)
Log of distance from community centre to population centre in kilometres	-0.00 (0.01)
Log of distance from community centre to major road in kilometres	0.00 (0.01)
Household head ethnicity	-0.00 (0.00)
Log of number of years the household lived in this place/district	-0.00 (0.01)
Log of annual precipitation in the community in millimetres	-0.02 (0.05)
Number of dependants in the household by household size	-0.02 (0.02)
Household members have never received school education (0=No, 1=Yes)	0.01 (0.01)

Tropic-cool/humid (0=No, 1=Yes)	-0.00 (0.01)
Share of land rainfed	-0.01 (0.03)
Share of land with sand loam	0.01 (0.02)
Share of land with good soil quality	-0.00 (0.02)
Parcel is flat (0=No, 1=Yes)	0.01 (0.01)
Slope of parcel is gentle (0=No, 1=Yes)	-0.02** (0.01)
Household had access to credit in 2009 (0=No, 1=Yes)	0.01 (0.01)
Seed was bought in local/village market (0=No, 1=Yes)	0.02** (0.01)
Household experienced drought/irregular rains (0=No, 1=Yes)	-0.00 (0.01)
Year is 2010 (0=No, 1=Yes)	-0.08*** (0.01)
Year is 2011 (0=No, 1=Yes)	-0.05*** (0.01)
Household lives in Western Region (0=No, 1=Yes)	0.01 (0.02)
Household lives in Northern Region (0=No, 1=Yes)	0.05*** (0.01)
Household lives in Central Region (0=No, 1=Yes)	0.03 (0.02)
Proportion of households adopting improved maize seeds in the community	0.34*** (0.02)
Log of distance from community centre to agricultural extension services in kilometres	0.01 (0.00)
Household had access to agricultural information from cooperative/farmers association or input supplier or large-scale farmer or an NGO	0.02 (0.02)
Household had access to agricultural information from NAADS in 2009	0.03** (0.01)
Mean of share of land rainfed	0.01 (0.05)
Mean of share of land with sand loam	-0.01 (0.02)
Mean of share of land with good soil quality	0.02 (0.03)
Mean of household experienced drought/irregular rains	0.02 (0.02)
Observations	2,568

Notes:

f. Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

g. LSMS Uganda, years 2009, 2010 and 2011.

h. Source: authors' estimations.

Second-stage estimation: results

We examine impact on welfare variables, namely, consumption expenditure first. In the LSMS surveys, expenditures are reported in the local currency (Ugandan shilling). Food expenditure (weekly), and expenditure on durable (monthly) and semi-durables goods (monthly) are also available. After constructing the consumption aggregate, these expenditure levels are converted into daily expenditure in US$ PPP per adult equivalent (with lower weightings assigned to children in the household).[13] Expenditure levels in local currency are converted to US$ PPP with World Bank Development Indicators 2014 data (World Bank, 2014). We derive total, non-food and food expenditures. Variables are log transformed to take into account the skewness of the expenditure distribution.

Using the US$ PPP constant daily total expenditure per adult equivalent at baseline (in 2009), the Foster-Greer-Thorbecke poverty measures are constructed, namely, the poverty headcount, poverty gap and poverty severity. Three different poverty lines (PLs) are employed and specifically:

- The median of the constant daily total expenditure per adult equivalent variable in 2009 ("50thPL"), about US$1.7 PPP.
- An international poverty line (constant daily total expenditure of US$2 PPP, "InternationalPL").
- The 60th percentile of the constant daily total expenditure per adult equivalent variable in 2009 ("60thPL"), about US$2.1 PPP.

Examining the impact of improved maize seeds at different poverty lines enables us to distinguish the expenditure levels at which greater poverty reduction takes place. Several measures of poverty are derived in order to see the impacts of agricultural technology on the proportion of poor people (poverty headcount), on the extent of the minimum transfers needed to end poverty (poverty gap), and on inequality within the poor (poverty severity) in the sample.

The impact of adoption on yields is explored via the value of agricultural production in Ugandan shillings and yields in kilograms in order to assess whether the uptake of agricultural technology increases the value of agricultural production as a whole, generating higher crop productivity and higher crop market sales or higher revenues due to increased quality and quantity of production. The latter should then influence consumption gains, income increases and, ultimately, poverty reduction. In order to smooth the variations, the agricultural variables are also log transformed.

We first present results from the main regression frameworks[14] (PSM, panel data estimators, Heckman selection model, ESRM and CF) employed to estimate the impact of agricultural technology adoption on the outcome variables of interest in Tables 6 and 7 for continuous and binary variables, respectively. In all frameworks, adoption of technology is defined as household use of improved maize seed varieties, and the models are run for households that grow maize in all years (balanced panel).

13. *Number of adults equivalent* = *Number of adults* + (0.5×*Number of children*)$^{0.8}$ (see Deaton and Zaidi, 2002).

14. For some of the estimation models, the use of IVs is required (except in PSM and panel data estimations). The kernel density graphs of adopters and non-adopters' propensity scores and the Rosenbaum and Rubin bias graph across the outcomes are available upon request.

Table 6 Summary of results in the second stage across estimations for continuous outcome variables

		PSM	Panel data (random effects) estimations	Panel data (fixed effects) estimations	Heckman selection model	ESRM[1]	CF
1	Log of daily constant total expenditure in US$ PPP per adult equivalent	0.12*** (0.03)	0.02 (0.03)	0.02 (0.02)	0.06*** (0.01)	0.16*** (0.02)	0.05 (0.06)
2	Log of daily constant non-food expenditure in US$ PPP per adult equivalent	0.09*** (0.03)	0.02 (0.02)	0.02 (0.02)	0.04*** (0.01)	0.06*** (0.02)	0.02 (0.06)
3	Log of daily constant food expenditure in US$ PPP per adult equivalent	0.10*** (0.03)	0.01 (0.03)	0.03 (0.02)	0.00 (0.01)	0.21*** (0.01)	0.08* (0.04)
4	Log of total agricultural yields in kilograms	-0.11 (0.08)	-0.17* (0.10)	-0.23** (0.11)	0.05*** (0.02)	0.13*** (0.03)	-0.16 (0.24)
5	Log of total value from agricultural production in constant Ugandan shillings	0.15 (0.09)	-0.01 (0.10)	-0.04 (0.09)	0.05* (0.03)	0.23*** (0.06)	-0.03 (0.21)

[1] In Tables 6 and 7, in order to calculate the impact of adoption technology on the log of constant daily expenditures per adult equivalent (in US$ PPP) for the ESRM, it is necessary to difference the expected value of this outcome in regime 1 with the expected value of this outcome in regime 2. The standard errors of the coefficients on adoption of technology are derived by a t-test of this difference.

Notes:

a. Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p<0.01$
b. LSMS Uganda, years 2009, 2010 and 2011.
c. Coefficients are average treatment effects on adopting households.
d. Source: authors' estimations.
e. Columns 2 and 3 (panel RE and panel FE) in Table 6 are estimated without the IVs. Thus, these models do not account for the endogeneity of adoption. The control function model (CF, column 6 in Table 6 and column 4 in Table 7) includes the IVs.

Table 7 Summary of results in the second stage across estimations for binary outcome variables

		PSM	Heckman selection model[1]	ESRM	CF
1	Poverty headcount (medianPL)	-0.08** (0.03)	-0.01 (0.01)	-0.24*** (0.02)	0.02* (0.01)
2	Poverty headcount (2 US$ PPP PL)	-0.07** (0.03)	-0.05*** (0.01)	-0.12*** (0.01)	-0.04*** (0.01)
3	Poverty headcount (60thPL)	-0.07** (0.03)	0.03*** (0.01)	-0.08*** (0.02)	-0.00 (0.01)

[1] In order to calculate the impact of adoption technology on the log of constant daily expenditures per adult equivalent (in US$ PPP) for the Heckman selection model, it is necessary to difference the probability of being poor when the household adopted and the probability of being poor when the household did not adopt. The standard errors of the coefficients on adoption of technology are derived by a t-test of this difference.

Notes:

a. Clustered standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01.
b. LSMS Uganda, years 2009, 2010 and 2011.
c. Coefficients are average treatment effects on adopting households.
d. Source: authors' estimations.

Focusing on the consumption expenditure and welfare outcomes (Tables 6 and 7), the non-corner solutions variables, we note that, across the various estimators, results point to the same direction but the magnitude differs. The magnitudes of coefficients are higher in the case of the ESRM, suggesting that selection on unobservables, when taken into account by modelling two different regimes, for adopters and non-adopters, increases impact estimates. Unobservable variables may include, for example, household head's farming ability, entrepreneurial initiative or risk aversion. Econometric approaches to deal with selection bias such as PSM only control for observed heterogeneity. Other approaches, although potentially taking into account unobserved heterogeneity such as the Heckman selection model, only assume one selection and outcome equation, thereby indicating that the impact can be represented as a simple parallel shift with respect to the outcome variable. Therefore, we consider the endogenous switching regression framework as our best estimator, as it estimates two separate equations (one for adopters, and one for non-adopters) along with the selection equation (e.g. Kassie et al., 2008; Di Falco, Veronesi and Yesuf, 2011). In addition, standard panel data estimators are potentially biased. This is because random effects do not assume the endogeneity of the adoption decision, and fixed effects only consider time-constant heterogeneity while assuming that there is no difference between farmers who adopt an improved variety and those who disadopt the improved variety.

In the case of the ESRM, we find that the constant daily total expenditure (in US$ PPP) of adopting households increased by 16 per cent. Similarly, for non-food and food expenditures, adoption resulted in a rise of 6 per cent and 21 per cent, respectively.

For the set of poverty headcount indices, using as poverty thresholds the 50th and 60th percentiles of constant daily total expenditure in US$ PPP, large poverty reduction impacts are found. Adoption of improved maize seeds led to a reduction in the likelihood of being poor across all poverty lines, namely, by 24, 12 and 8 per cent when choosing the 50thPL (equivalent to US$1.7 PPP a day), the US$2 PPP, and the 60thPL (equivalent to US$2.1 PPP a day).

These welfare improvements most probably took place through a rise in yields, where adoption of improved maize seeds led to a 13 per cent rise in agricultural yields and a 23 per cent increase in the total value of agricultural production, as shown in Table 8. The difference in the increase in total yields and total value of production from adoption of improved maize seeds could be attributed to a rise in agricultural prices over time.

Table 8 ESR-based average treatment effect on adopting households (ATT) of adoption of improved maize seeds

		Decision to adopt	Decision not to adopt	ATT	N
1	Log of daily constant total expenditure in US$ PPP per adult equivalent	1.19	1.03	0.16*** (0.02)	2361
2	Log of daily constant non-food expenditure in US$ PPP per adult equivalent	0.78	0.72	0.06*** (0.02)	2361
3	Log of daily constant food expenditure in US$ PPP per adult equivalent	0.73	0.52	0.21*** (0.01)	2361
4	Poverty headcount (medianPL)	0.39	0.62	-0.24*** (0.02)	2361
5	Poverty headcount (2 US$ PPP PL)	0.45	0.57	-0.12*** (0.01)	2361
6	Poverty headcount (60thPL)	0.51	0.58	-0.08*** (0.02)	2361
7	Log of total agricultural yields in kgs	6.22	6.09	0.13*** (0.03)	1281
8	Log of total value from agricultural production in constant Ugandan shillings	14.32	14.09	0.23*** (0.06)	1281

Notes:

a. Clustered standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01.
b. LSMS Uganda, years 2009, 2010 and 2011.
c. Coefficients are average treatment effects on adopting households, except for outcomes 4, 5 and 6, which are average partial effects.
d. Source: authors' estimations.

Last, we examine the full ESRM estimation results for selected outcomes, such as the log of constant daily total expenditure per adult equivalent (in US$ PPP) and the poverty headcount (in the case of the median PL), Tables 9 and 10, respectively. Tables 11 and 12 show the full ESRM estimations for the log of total agricultural yields in kilograms and log of total value from agricultural production in constant Ugandan shillings.[15] The first column shows the estimation of the outcome in the first regime (adopting households) and the second column reports the results from the estimation for non-adopting households. The last column – "Household adopts improved maize seeds (0=No, 1=Yes)" – displays the estimation of the determinants of agricultural technology adoption, the first-stage regression. The coefficients are average partial effects.

Table 9 ESRM estimation of the log of daily constant total expenditure per adult equivalent (in US$ PPP)

	Log of daily constant total expenditure in US$ PPP per adult equivalent for adopting households (regime 1)	Log of daily constant total expenditure in US$ PPP per adult equivalent for non-adopting households (regime 2)	Household adopts improved maize seeds (0=No, 1=Yes)
Proportion of households adopting improved maize seeds in the community			0.36*** (0.02)
Log of distance from community centre to agricultural extension services in kilometres			0.00 (0.01)
Durable and household asset index (predicted with 2009 data)	1.68*** (0.25)	1.90*** (0.13)	0.03 (0.05)
Sex of household head is female (0=No, 1=Yes)	-0.22*** (0.08)	-0.08*** (0.03)	-0.02* (0.01)
Age of household head in years	0.00 (0.00)	0.00*** (0.00)	-0.00 (0.00)
Log of distance from community centre to population centre in kilometres	-0.05 (0.04)	-0.08*** (0.02)	-0.01 (0.01)
Log of distance from community centre to major road in kilometres	-0.03 (0.03)	-0.01 (0.02)	0.00 (0.01)
Household head ethnicity	0.00** (0.00)	0.00 (0.00)	-0.00 (0.00)
Log of number of years the household lived in this place/district	0.01 (0.03)	-0.03* (0.02)	-0.00 (0.01)
Log of annual precipitation in the community in millimetres	-0.30 (0.20)	-0.04 (0.14)	-0.03 (0.04)
Number of dependants in the household by household size	-0.22 (0.19)	-0.08 (0.06)	-0.03 (0.02)

15. The coefficients, standard errors, number of observations and mean of control group for each estimation model are available upon request. In this paper, Appendix 1 presents the results from the CRC model, and Appendix 2 presents a table with the CF estimates. The ESRM estimations with all covariates are located in Table 9 for the outcome variable log of daily constant total expenditure in US$ PPP per adult equivalent, Table 10 for outcome variable poverty headcount (medianPL), Table 11 for outcome variable log of total agricultural yields in kilograms, and Table 12 for outcome variable log of total value from agricultural production in constant Ugandan shillings.

Household members have never received school education (0=No, 1=Yes)	-0.13** (0.06)	-0.06** (0.03)	0.01 (0.01)
Tropic-cool/humid (0=No, 1=Yes)	-0.10* (0.05)	-0.05 (0.04)	-0.01 (0.01)
Share of land rainfed	0.02 (0.08)	0.01 (0.04)	-0.00 (0.01)
Share of land with sand loam	0.06 (0.07)	-0.02 (0.03)	0.01 (0.01)
Share of land with good soil quality	0.08 (0.07)	0.04 (0.03)	0.01 (0.01)
Parcel is flat (0=No, 1=Yes)	-0.01 (0.06)	-0.05* (0.03)	0.00 (0.01)
Slope of parcel is gentle (0=No, 1=Yes)	0.04 (0.04)	-0.00 (0.02)	-0.03** (0.01)
Household had access to credit in 2009 (0=No, 1=Yes)	-0.10* (0.05)	0.05** (0.02)	0.01 (0.01)
Seed was bought in local/village market (0=No, 1=Yes)	-0.10** (0.05)	0.02 (0.02)	0.02** (0.01)
Household experienced drought/irregular rains (0=No, 1=Yes)	-0.00 (0.06)	0.04* (0.02)	0.00 (0.01)
Year is 2010 (0=No, 1=Yes)	-0.02 (0.10)	0.03 (0.02)	-0.08*** (0.01)
Year is 2011 (0=No, 1=Yes)	-0.12 (0.10)	0.03 (0.03)	-0.06*** (0.01)
Household lives in Western Region (0=No, 1=Yes)	-0.35*** (0.11)	-0.12** (0.05)	0.02 (0.02)
Household lives in Northern Region (0=No, 1=Yes)	-0.06 (0.07)	-0.00 (0.04)	0.06*** (0.01)
Household lives in Central Region (0=No, 1=Yes)	0.04 (0.08)	0.04 (0.05)	0.03 (0.02)
Household had access to agricultural information from cooperative/farmers association or input supplier or large-scale farmer or an NGO	0.01 (0.06)	0.03 (0.03)	0.02*** (0.01)
Household had access to agricultural information from NAADS	0.14** (0.07)	0.09*** (0.03)	0.03** (0.01)
Lagged adoption of improved maize seeds (0=No, 1=Yes)	0.05 (0.09)	0.06 (0.07)	0.18*** (0.02)
Initial adoption of improved maize seeds (0=No, 1=Yes)	0.01 (0.06)	0.13*** (0.05)	0.11*** (0.01)
Mean of non-adopters	1.05		
Observations	2,361		

Notes:

a. Clustered standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.

b. LSMS Uganda, years 2009, 2010 and 2011.

c. Source: authors’ estimations.

Table 10 ESRM estimation of the poverty headcount (medianPL)

	Poverty headcount (medianPL) for adopting households (regime 1)	Poverty headcount (medianPL) for non-adopting households (regime 2)	Household adopts improved maize seeds (0=No, 1=Yes)
Proportion of households adopting improved maize seeds in the community			0.36*** (0.02)
Log of distance from community centre to agricultural extension services in kilometres			0.00 (0.01)
Durable and household asset index (predicted with 2009 data)	-1.04*** (0.20)	-1.30*** (0.12)	0.03 (0.05)
Sex of household head is female (0=No, 1=Yes)	0.22*** (0.07)	0.07*** (0.03)	-0.02* (0.01)
Age of household head in years	-0.00 (0.00)	-0.00*** (0.00)	-0.00 (0.00)
Log of distance from community centre to population centre in kilometres	0.12*** (0.03)	0.09*** (0.02)	-0.01 (0.01)
Log of distance from community centre to major road in kilometres	0.00 (0.03)	0.01 (0.02)	0.00 (0.01)
Household head ethnicity	-0.00*** (0.00)	-0.00 (0.00)	-0.00 (0.00)
Log of number of years the household lived in this place/district	-0.00 (0.03)	0.02 (0.02)	-0.00 (0.01)
Log of annual precipitation in the community in millimetres	0.12 (0.22)	0.10 (0.15)	-0.03 (0.04)
Number of dependants in the household by household size	0.15 (0.15)	0.05 (0.07)	-0.03 (0.02)
Household members have never received school education (0=No, 1=Yes)	0.12** (0.06)	0.08*** (0.03)	0.01 (0.01)
Tropic-cool/humid (0=No, 1=Yes)	0.15*** (0.05)	0.02 (0.04)	-0.01 (0.01)
Share of land rainfed	0.03 (0.08)	-0.01 (0.04)	-0.00 (0.01)
Share of land with sand loam	0.01 (0.08)	0.02 (0.04)	0.01 (0.01)
Share of land with good soil quality	-0.12* (0.07)	0.01 (0.03)	0.01 (0.01)
Parcel is flat (0=No, 1=Yes)	0.03 (0.06)	0.04 (0.03)	0.00 (0.01)

Slope of parcel is gentle (0=No, 1=Yes)	0.01 (0.05)	-0.00 (0.03)	-0.03** (0.01)
Household had access to credit in 2009 (0=No, 1=Yes)	0.06 (0.05)	-0.05* (0.03)	0.01 (0.01)
Seed was bought in local/village market (0=No, 1=Yes)	0.05 (0.05)	-0.02 (0.03)	0.02** (0.01)
Household experienced drought/irregular rains (0=No, 1=Yes)	0.03 (0.06)	-0.02 (0.02)	0.00 (0.01)
Year is 2010 (0=No, 1=Yes)	0.01 (0.11)	-0.06** (0.03)	-0.08*** (0.01)
Year is 2011 (0=No, 1=Yes)	0.10 (0.10)	-0.04 (0.03)	-0.06*** (0.01)
Household lives in Western Region (0=No, 1=Yes)	0.62*** (0.15)	0.10** (0.05)	0.02 (0.02)
Household lives in Northern Region (0=No, 1=Yes)	0.19*** (0.07)	0.00 (0.04)	0.06*** (0.01)
Household lives in Central Region (0=No, 1=Yes)	0.04 (0.07)	-0.05 (0.05)	0.03 (0.02)
Household had access to agricultural information from cooperative/farmers association or input supplier or large-scale farmer or an NGO	-0.10 (0.07)	-0.03 (0.04)	0.02*** (0.01)
Household had access to agricultural information from NAADS	-0.12 (0.07)	-0.06* (0.03)	0.03** (0.01)
Lagged adoption of improved maize seeds (0=No, 1=Yes)	-0.05 (0.09)	-0.04 (0.08)	0.18*** (0.02)
Initial adoption of improved maize seeds (0=No, 1=Yes)	-0.01 (0.06)	-0.13*** (0.04)	0.11*** (0.01)
Mean of non-adopters	0.51		
Observations	2,361		

Notes:

a. Clustered standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.

b. LSMS Uganda, years 2009, 2010 and 2011.

c. Source: authors’ estimations.

Table 11 ESRM estimation of the log of total agricultural yields in kilograms

	Log of total agricultural yields in kilograms for adopting households (regime 1)	Log of total agricultural yields in kilograms for non-adopting households (regime 2)	Household adopts improved maize seeds (0=No, 1=Yes)
Proportion of households adopting improved maize seeds in the community			0.47*** (0.02)
Log of distance from community centre to agricultural extension services in kilometres			0.00 (0.01)
Durable and household asset index (predicted with 2009 data)	1.56*** (0.49)	1.22*** (0.39)	0.06 (0.06)
Sex of household head is female (0=No, 1=Yes)	-0.56*** (0.19)	-0.05 (0.08)	-0.03*** (0.01)
Age of household head in years	-0.01 (0.00)	-0.00 (0.00)	0.00 (0.00)
Log of distance from community centre to population centre in kilometres	0.19** (0.08)	0.05 (0.07)	-0.01 (0.01)
Log of distance from community centre to major road in kilometres	-0.03 (0.06)	-0.02 (0.05)	0.00 (0.01)
Household head ethnicity	0.01*** (0.00)	0.00 (0.00)	-0.00 (0.00)
Log of number of years the household lived in this place/district	0.04 (0.07)	0.00 (0.07)	-0.02** (0.01)
Log of annual precipitation in the community in millimetres	0.89* (0.53)	-0.04 (0.39)	-0.04 (0.12)
Number of dependants in the household by household size	0.59* (0.33)	0.06 (0.17)	-0.03 (0.03)
Household members have never received school education (0=No, 1=Yes)	-0.20* (0.12)	-0.04 (0.09)	0.02 (0.02)
Tropic-cool/humid (0=No, 1=Yes)	0.02 (0.14)	0.07 (0.10)	0.00 (0.02)
Share of land rainfed	-0.45** (0.19)	0.25** (0.11)	-0.00 (0.03)
Share of land with sand loam	-0.04 (0.15)	0.04 (0.10)	0.01 (0.03)
Share of land with good soil quality	0.14 (0.15)	0.05 (0.08)	0.01 (0.03)

Parcel is flat (0=No, 1=Yes)	0.32* (0.17)	0.18* (0.09)	-0.01 (0.02)
Slope of parcel is gentle (0=No, 1=Yes)	-0.05 (0.14)	0.08 (0.09)	-0.04* (0.02)
Household had access to credit in 2009 (0=No, 1=Yes)	-0.05 (0.12)	0.07 (0.08)	-0.00 (0.01)
Seed was bought in local/village market (0=No, 1=Yes)	-0.03 (0.12)	-0.01 (0.07)	0.04** (0.02)
Household experienced drought/irregular rains (0=No, 1=Yes)	-0.10 (0.15)	-0.10 (0.09)	0.02 (0.02)
Year is 2010 (0=No, 1=Yes)	-0.02 (0.21)	-0.01 (0.10)	-0.10*** (0.03)
Year is 2011 (0=No, 1=Yes)	-0.17 (0.24)	-0.10 (0.11)	-0.07* (0.04)
Household lives in Western Region (0=No, 1=Yes)	0.52 (0.48)	0.22 (0.14)	0.06 (0.05)
Household lives in Northern Region (0=No, 1=Yes)	-0.47*** (0.15)	-0.12 (0.14)	0.08*** (0.03)
Household lives in Central Region (0=No, 1=Yes)	-0.02 (0.21)	0.00 (0.14)	0.05 (0.04)
Household had access to agricultural information from cooperative/farmers association or input supplier or large-scale farmer or an NGO	-0.03 (0.14)	-0.01 (0.13)	0.02 (0.01)
Household had access to agricultural information from NAADS	-0.12 (0.11)	0.04 (0.10)	0.03* (0.02)
Lagged adoption of improved maize seeds (0=No, 1=Yes)	0.07 (0.25)	0.03 (0.24)	0.24*** (0.01)
Initial adoption of improved maize seeds (0=No, 1=Yes)	-0.04 (0.14)	0.06 (0.16)	0.13*** (0.01)
Mean of non-adopters	6.31		
Observations	1,281		

Notes:

a. Clustered standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.

b. LSMS Uganda, years 2009, 2010 and 2011.

c. Source: authors’ estimations.

Table 12 ESRM estimation of the log of total value from agricultural production in constant Ugandan shillings

	Log of total value from agricultural production in constant Ugandan shillings for adopting households (regime 1)	Log of total value from agricultural production in constant Ugandan shillings for non-adopting households (regime 2)	Household adopts improved maize seeds (0=No, 1=Yes)
Proportion of households adopting improved maize seeds in the community			0.47*** (0.02)
Log of distance from community centre to agricultural extension services in kilometres			0.00 (0.01)
Durable and household asset index (predicted with 2009 data)	2.73*** (0.66)	1.41*** (0.46)	0.06 (0.06)
Sex of household head is female (0=No, 1=Yes)	-1.00*** (0.22)	-0.26*** (0.08)	-0.03*** (0.01)
Age of household head in years	-0.01* (0.01)	-0.00 (0.00)	0.00 (0.00)
Log of distance from community centre to population centre in kilometres	0.13 (0.12)	0.26*** (0.08)	-0.01 (0.01)
Log of distance from community centre to major road in kilometres	0.10 (0.11)	-0.05 (0.06)	0.00 (0.01)
Household head ethnicity	0.01 (0.01)	0.01** (0.00)	-0.00 (0.00)
Log of number of years the household lived in this place/district	0.00 (0.11)	0.06 (0.07)	-0.02** (0.01)
Log of annual precipitation in the community in millimetres	-0.60 (0.73)	0.17 (0.41)	-0.04 (0.12)
Number of dependants in the household by household size	-0.02 (0.33)	0.00 (0.18)	-0.03 (0.03)
Household members have never received school education (0=No, 1=Yes)	-0.04 (0.16)	-0.13 (0.08)	0.02 (0.02)
Tropic-cool/humid (0=No, 1=Yes)	0.09 (0.19)	-0.12 (0.10)	0.00 (0.02)
Share of land rainfed	-0.91*** (0.24)	-0.39*** (0.14)	-0.00 (0.03)
Share of land with sand loam	-0.25 (0.20)	-0.05 (0.11)	0.01 (0.03)

Share of land with good soil quality	0.29 (0.19)	0.15 (0.10)	0.01 (0.03)
Parcel is flat (0=No, 1=Yes)	0.13 (0.20)	0.03 (0.10)	-0.01 (0.02)
Slope of parcel is gentle (0=No, 1=Yes)	-0.13 (0.15)	0.07 (0.08)	-0.04* (0.02)
Household had access to credit in 2009 (0=No, 1=Yes)	-0.09 (0.15)	0.12 (0.09)	-0.00 (0.01)
Seed was bought in local/village market (0=No, 1=Yes)	-0.08 (0.17)	0.07 (0.08)	0.04** (0.02)
Household experienced drought/irregular rains (0=No, 1=Yes)	0.04 (0.16)	0.00 (0.08)	0.02 (0.02)
Year is 2010 (0=No, 1=Yes)	-0.74*** (0.26)	-0.27*** (0.09)	-0.10*** (0.03)
Year is 2011 (0=No, 1=Yes)	-1.34*** (0.29)	-0.75*** (0.10)	-0.07* (0.04)
Household lives in Western Region (0=No, 1=Yes)	1.10*** (0.29)	0.53*** (0.17)	0.06 (0.05)
Household lives in Northern Region (0=No, 1=Yes)	-0.25 (0.22)	-0.46*** (0.15)	0.08*** (0.03)
Household lives in Central Region (0=No, 1=Yes)	0.14 (0.29)	0.41*** (0.14)	0.05 (0.04)
Household had access to agricultural information from cooperative/farmers association or input supplier or large-scale farmer or an NGO	0.28 (0.20)	0.29** (0.14)	0.02 (0.01)
Household had access to agricultural information from NAADS	0.30** (0.14)	0.15 (0.10)	0.03* (0.02)
Lagged adoption of improved maize seeds (0=No, 1=Yes)	0.09 (0.27)	0.37* (0.21)	0.24*** (0.01)
Initial adoption of improved maize seeds (0=No, 1=Yes)	0.16 (0.17)	0.13 (0.19)	0.13*** (0.01)
Mean of non-adopters	14.19		
Observations	1,281		

Notes:

a. Clustered standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.

b. LSMS Uganda, years 2009, 2010 and 2011.

c. Source: authors' estimations.

Looking at the two different regimes, we can see that asset levels in 2009 positively affected expenditure levels of adopters. In the case of adopters and non-adopters, however, being a female-headed household negatively affected expenditure levels (Table 9), with a larger coefficient for adopters. Regional heterogeneity seems to be an important determinant, where adopting households in Western Region decreased their total expenditure by 35 per cent relative to those in Eastern Region and non-adopting farmers by 12 per cent. Receiving advice from NAADS in 2009 significantly increased expenditure levels for adopters and also those that eventually disadopted in later periods.

In the case of the incidence of poverty (Table 10), structural conditions such as asset endowments seem to be determining factors reducing the probability of being poor for non-adopters relative to adopters. State dependence and initial adoption status are strongly related to current adoption status, corroborating the importance of this variable and the need to factor it into the specifications of interest. We can see that initial adoption (in 2009) is correlated with higher expenditure levels for those who chose not to adopt (e.g. disadopted in later periods, Table 9). This is corroborated by the correlation between the adoption choice equation and the log of the constant daily total expenditure per adult equivalent equation for non-adopters (rho2), which is positive but not statistically significantly different from zero. Rho1 (the correlation between the adoption choice equation and the log of the constant daily total expenditure per adult equivalent equation for adopters) is not statistically significant for the equation for adopting households (Table 13). In addition, the correlation between the adoption choice equation and the poverty lines for non-adopters (rho2) is negative and not significantly different from zero (for the poverty models), except for the poverty headcount set at US$2 PPP per capita per day. They are not statistically significant for the equation for adopting households. The model suggests that households that do not adopt improved maize seeds are more likely to be poor than a random household from the sample would be, and those adopting do no better or worse than a random household. Also, if we look at the coefficients for initial adoption, this is only significant for the non-adopter regime and inversely related to the proportion of poor among those who do not adopt (hence, at later periods). In fact, initial adoption led to reduced poverty among those who disadopted in later periods by 13 per cent (statistically significant).

As far as agricultural outcome variables are concerned, we find that the log of total agricultural yields in kilograms and log of total value from agricultural production in constant Ugandan shillings increased with adoption of improved maize seeds by 13 and 23 per cent (Table 8), respectively.

Impact estimates and treatment effects that assume homogeneity and selection based on observables based on PSM are not significant for agricultural outcomes. FE models assume negative returns on yields. Heckman-type models and the ESRM instead show positive returns once selection on unobservables is factored in.

Turning to the last full ESRM results (Tables 11 and 12) for the agricultural outcomes as a whole, we find that for the log of total agricultural yields in kilograms, initial endowments (assets) and education are positively related to higher yields for adopters (Table 11). Being in Northern Region decreases returns by 47 per cent for adopters, although this variable was positively related to current adoption in the first-stage equation. Relative to the second agricultural outcome (Table 12), the log of total value from agricultural production in constant Ugandan shillings, there is a larger negative time trend for adopters, negatively affecting agricultural revenues in later years. Having benefited from access to NAADS-specific agricultural information in 2009 also remains an important determinant (30 per cent higher agricultural revenues for adopting households).

We then investigate the role of adoption of improved maize seeds on improved maize seeds specific agricultural outcomes through DH (Verkaart et al., 2017), the suitable models for variables that present a corner solution. Table 14 shows the average partial effect of improved maize seeds using CF combined with CRE and DH.

Table 13 Correlation between the adoption choice equation and the outcome of interest in the ESRM estimations

			Coefficient	Standard error
1	Log of daily constant total expenditure in US$ PPP per adult equivalent	Rho1	0.09	0.14
		Rho2	-0.03	0.09
2	Log of daily constant non-food expenditure in US$ PPP per adult equivalent	Rho1	0.06	0.13
		Rho2	0.03	0.16
3	Log of daily constant food expenditure in US$ PPP per adult equivalent	Rho1	0.09	0.12
		Rho2	0.25	0.13
4	Log of total agricultural yields in kilograms	Rho1	0.00	0.10
		Rho2	0.20	0.13
5	Log of total value from agricultural production in constant Ugandan shillings	Rho1	0.17	0.14
		Rho2	0.14	0.12
6	Poverty headcount (medianPL)	Rho1	-0.14	0.13
		Rho2	-0.25	0.16
7	Poverty headcount (US$2 PPP PL)	Rho1	-0.07	0.14
		Rho2	-0.30	0.14**
8	Poverty headcount (60thPL)	Rho1	0.04	0.12
		Rho2	-0.19	0.13

Notes:
a. Clustered standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.
b. LSMS Uganda, years 2009, 2010 and 2011.
c. Source: authors' estimations.

Table 14 Summary of results in double-hurdle estimations

		Average partial effect	Mean of outcome variables	Percentage increase
1	Yields from improved maize seeds in kilograms	61.71*** (4.18)	310.98	21.85
2	Value of production from improved maize seeds in constant Ugandan shillings	104,327.6*** (6,768.61)	392,786	28.38

Notes:
a. Clustered standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01.
b. LSMS Uganda, years 2009, 2010 and 2011.
c. Source: authors' estimations.

Tables 15 and 16 present the full estimation results for the DH estimation. Here, we kept the observations with no improved maize production, which explains the slightly higher number of observations in the sample (1,320 relative to 1,281). We find that adoption of improved maize seeds results in a statistically significant increase in yields and value of maize production. These results are in line with those of the previous estimations in terms of sign and magnitude. They further strengthen the hypothesis that these improved seeds contributed to poverty reduction through an increase in maize production.

Table 15 Double-hurdle estimation of the yields from improved maize seeds, in kilograms

	Household adopts improved maize seeds (0=No, 1=Yes)	**Yield from improved maize seeds in kilograms**
	Tier 1 (probit estimation)	Tier 2 (truncated normal estimation)
Proportion of households adopting improved maize seeds in the community	0.43*** (0.03)	
Log of distance from community centre to agricultural extension services in kilometres	0.01 (0.01)	
Durable and household asset index (predicted with 2009 data)	0.06 (0.06)	1,026.06 (923.61)
Sex of household head is female (0=No, 1=Yes)	-0.02 (0.01)	-905.33** (451.92)
Age of household head in years	0.00 (0.00)	-10.65 (9.91)
Log of distance from community centre to population centre in kilometres	-0.01 (0.02)	161.85 (188.76)
Log of distance from community centre to major road in kilometres	0.00 (0.01)	-154.08 (134.15)
Household head ethnicity	-0.00 (0.00)	-0.93 (8.00)
Log of number of years the household lived in this place/district	-0.03*** (0.01)	-35.15 (158.57)
Log of annual precipitation in the community in millimetres	-0.03 (0.05)	-721.28 (1,121.22)
Number of dependants in the household by household size	-0.01 (0.04)	-511.21 (547.58)
Household members have never received school education (0=No, 1=Yes)	0.01 (0.02)	-162.81 (248.99)
Tropic-cool/humid (0=No, 1=Yes)	0.00 (0.02)	248.18 (241.54)
Share of land rainfed	-0.00 (0.05)	-377.79 (527.24)
Share of land with sand loam	0.02 (0.03)	185.80 (397.73)

Share of land with good soil quality	0.01 (0.03)	-200.50 (336.87)
Parcel is flat (0=No, 1=Yes)	-0.01 (0.03)	653.95* (353.31)
Slope of parcel is gentle (0=No, 1=Yes)	-0.03* (0.02)	-39.97 (225.68)
Household had access to credit in 2009 (0=No, 1=Yes)	-0.00 (0.02)	-443.89* (256.77)
Seed was bought in local/village market (0=No, 1=Yes)	0.03** (0.01)	-616.74** (296.92)
Household experienced drought/irregular rains (0=No, 1=Yes)	0.01 (0.02)	419.47 (328.59)
Year is 2010 (0=No, 1=Yes)	-0.08*** (0.03)	-534.04 (443.88)
Year is 2011 (0=No, 1=Yes)	-0.05** (0.02)	-1,669.41** (685.34)
Household lives in Western Region (0=No, 1=Yes)	0.05 (0.05)	-180.53 (932.99)
Household lives in Northern Region (0=No, 1=Yes)	0.08*** (0.03)	461.74 (354.66)
Household lives in Central Region (0=No, 1=Yes)	0.04** (0.02)	-20.20 (384.59)
Household had access to agricultural information from cooperative/farmers association or input supplier or large-scale farmer or an NGO	0.01 (0.02)	140.08 (297.93)
Household had access to agricultural information from NAADS	0.03* (0.02)	-109.50 (260.42)
Lagged adoption of improved maize seeds (0=No, 1=Yes)	0.23*** (0.02)	549.96 (400.33)
Initial adoption of improved maize seeds (0=No, 1=Yes)	0.12*** (0.01)	297.69 (251.19)
Mean of share of land rainfed	0.05 (0.05)	1,115.00 (855.67)
Mean of share of land with sand loam	-0.05 (0.04)	-29.54 (663.68)
Mean of share of land with good soil quality	-0.00 (0.03)	615.51 (591.37)
Mean of household experienced drought/irregular rains	0.01 (0.04)	-733.36 (590.68)
Observations	1,320	228

Notes:

a. Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

b. LSMS Uganda, years 2009, 2010 and 2011.

c. Source: authors' estimations.

Table 16 Double hurdle estimation of the value of production from improved maize seeds, in constant Ugandan shillings

	Household adopts improved maize seeds (0=No, 1=Yes)	Value of improved maize seeds production in constant Ugandan shillings
	Tier 1 (probit estimation)	Tier 2 (truncated normal estimation)
Proportion of households adopting improved maize seeds in the community	0.43*** (0.03)	
Log of distance from community centre to agricultural extension services in kilometres	0.01 (0.01)	
Durable and household asset index (predicted with 2009 data)	0.06 (0.06)	1,846,409.01** (753,376.56)
Sex of household head is female (0=No, 1=Yes)	-0.02 (0.01)	-1,126,222.76*** (351,056.25)
Age of household head in years	0.00 (0.00)	-3,015.53 (6,875.00)
Log of distance from community centre to population centre in kilometres	-0.01 (0.02)	239,502.76 (159,215.89)
Log of distance from community centre to major road in kilometres	0.00 (0.01)	22,682.76 (98,687.48)
Household head ethnicity	-0.00 (0.00)	-6,389.85 (6,627.05)
Log of number of years the household lived in this place/district	-0.03*** (0.01)	-82,603.23 (128,321.10)
Log of annual precipitation in the community in millimetres	-0.03 (0.05)	-1,713,105.83* (990,817.43)
Number of dependants in the household by household size	-0.01 (0.04)	624,158.36 (455,253.49)
Household members have never received school education (0=No, 1=Yes)	0.01 (0.02)	-193,409.92 (185,730.14)
Tropic-cool/humid (0=No, 1=Yes)	0.00 (0.02)	236,021.12 (198,791.14)
Share of land rainfed	-0.00 (0.05)	-862,680.87** (405,608.60)
Share of land with sand loam	0.02 (0.03)	230,548.27 (312,211.12)
Share of land with good soil quality	0.01 (0.03)	266,221.29 (258,414.52)

Parcel is flat (0=No, 1=Yes)	-0.01 (0.03)	627,612.97** (287,164.80)
Slope of parcel is gentle (0=No, 1=Yes)	-0.03* (0.02)	-20,524.04 (159,832.17)
Household had access to credit in 2009 (0=No, 1=Yes)	-0.00 (0.02)	-472,554.78** (187,602.33)
Seed was bought in local/village market (0=No, 1=Yes)	0.03** (0.01)	-221,226.36 (191,020.92)
Household experienced drought/irregular rains (0=No, 1=Yes)	0.01 (0.02)	-33,632.27 (240,656.50)
Year is 2010 (0=No, 1=Yes)	-0.08*** (0.03)	-2,069,701.63*** (563,005.66)
Year is 2011 (0=No, 1=Yes)	-0.05** (0.02)	-2,144,395.61*** (572,071.73)
Household lives in Western Region (0=No, 1=Yes)	0.05 (0.05)	1,555,514.42** (707,775.21)
Household lives in Northern Region (0=No, 1=Yes)	0.08*** (0.03)	257,735.36 (271,755.27)
Household lives in Central Region (0=No, 1=Yes)	0.04** (0.02)	-317,700.59 (310,013.36)
Household had access to agricultural information from cooperative/farmers association or input supplier or large-scale farmer or an NGO	0.01 (0.02)	-403,881.24 (258,781.61)
Household had access to agricultural information from NAADS	0.03* (0.02)	106,158.10 (185,031.53)
Lagged adoption of improved maize seeds (0=No, 1=Yes)	0.23*** (0.02)	481,777.11 (418,744.00)
Initial adoption of improved maize seeds (0=No, 1=Yes)	0.12*** (0.01)	962,345.74*** (280,386.60)
Mean of share of land rainfed	0.05 (0.05)	1,851,637.96*** (644,321.52)
Mean of share of land with sand loam	-0.05 (0.04)	-1,019,580.49* (532,722.36)
Mean of share of land with good soil quality	-0.00 (0.03)	-481,930.34 (466,551.44)
Mean of household experienced drought/irregular rains	0.01 (0.04)	-146,473.97 (411,399.28)
Observations	1,320	228

Notes:

a. Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

b. LSMS Uganda, years 2009, 2010 and 2011.

c. Source: authors' estimations.

Full DH estimations are provided in Tables 15 and 16 for the yields in kilograms and the value of production in constant Ugandan shillings, respectively, from using improved maize seeds. In the first hurdle, we identify that the same factors explaining adoption of improved maize seeds as highlighted in the first-stage results (Table 5), and there is strong internal coherence across parameters throughout the specifications. In the second hurdle, where the outcome is the yields in kilograms from improved maize seeds, the residual from the first stage is no longer statistically significant, indicating that adoption of improved maize seeds is no longer endogenous once the decision to adopt improved maize seeds has been made (therefore, we do not include it in the second hurdle, and the results do not change). Table 15 also indicates that gender differences are an important determinant, with female-headed households exhibiting lower yields. Relative to steep parcels, having flat land increases yields. However, having had access to credit in 2009 has a negative impact on the value of improved maize seeds. This may suggest that returns are a function of liquidity constraints. Turning to the value of production from improved maize seeds, we find the same patterns as seen in the previous table, with the negative time trend figuring prominently and being statistically significant, as well as variables related to liquidity constraints and accessibility of the seed locally, which figure as important determinants of adopting improved maize seeds. As always, we find that initial adoption in 2009 was positively related to revenues from improved maize seeds in the second tier.

Last, given that we observed results where state dependence is highly significant throughout all specifications (implying that the current adoption decision process is strongly influenced by past adoption), and that welfare returns and the extent of poverty reduction seem to be a function of the decision to adopt, we investigate the hypothesis of heterogeneous returns to adoption by presenting the results from the Suri (2011) CRC (Appendix 1).

This last analysis allows us to assess whether returns are indeed a function of the history of adoption. We find that when looking at outcomes in terms of total maize yields (in kilograms), the aggregate returns on yields are positive and statistically significant. However, this finding indicates that the returns are independent of the technology, e.g. the improved seeds (in other words, they are uncorrelated), and that there is no selection and heterogeneity across the different adoption history patterns. When we turn to poverty outcomes (Appendix 1), we find that there is indeed endogenous selection (this was also present in the ESRM). In other words, here the aggregate return is positive (i.e. the poverty headcount decreases), but the individual returns are negative and significant, hence, conditional on the adoption history, corroborating the heterogeneity hypothesis. Here, the negative coefficient implies that farmers who initially adopted had the highest poverty reduction by switching from being an early adopter to a disadopter. According to Figure A1.2, the highest poverty reduction gains were observed among those that exhibited a switching behaviour (mixed adopters and disadopters), possibly to counteract the unobservable shocks in this panel data. Shocks leading to a fall in the returns from improved maize, such as a decline in the price of maize, a reduction in household maize output, or a rise in the price of improved maize seeds, could explain this heterogeneity in the poverty impacts. In 2010, we know that NAADS's operations were suspended for five months and that there was a devastating drought. As shown in Table 1, persistence of adoption occurred to a lesser extent after 2010, most probably due to these shocks. However, the quality of the data prevents us from conducting further analysis on disadoption. A panel dataset with more variables on prices and shocks, and with further rounds, would allow further research on the matter. It is likely that we would see further disadoption in the years after 2011 due to these shocks, as distinguished in Kijima, Otsuka and Sserunkuuma (2011), where farmers massively disadopted in the presence of low profitability of improved seeds.

6 Concluding observations

Focusing on the role of agricultural research embodied in improved maize seeds, we investigated the determinants of adoption, and assessed the impact of adoption on welfare and agricultural outcomes in Uganda. The analysis was based on the LSMS-ISA household panel survey for three years (2009/10, 2010/11 and 2011/12).

An important point of departure of the present study from existing literature is, first, the robust econometric analysis of technology adoption in a dynamic setting that allows for state dependence, while taking into account selection and unobserved heterogeneity. To the best of our knowledge, state dependence has not been analysed in sufficient detail as a determinant explaining the impact heterogeneity. State dependence in the adoption decision process is in fact robustly established through the model presented and is statistically significant, after controlling for several factors. Adopting households were 17 per cent more likely to continue to adopt in the following year.

Second, we further contribute to the literature and policy debates by assessing the impact of improved seeds on welfare, poverty and agricultural outcomes, such as maize and total yields in Uganda. There is a significant positive effect on per adult equivalent expenditure, and significant poverty reduction for adopting households. Results across the different estimators present the same direction, with the ESRM exhibiting the larger magnitudes in the coefficients of interest. Once we take into account time-invariant unobserved heterogeneity, we find that results are consistently positive, compared with FE models where only time-constant heterogeneity is factored in.

Focusing on the ESRM results, the latter indicate that constant daily total per adult expenditure expressed in US$ PPP increased by 16 per cent (and non-food and food expenditure increased by 6 and 21 per cent, respectively) for adopters relative to non-adopters. Adoption of improved maize seeds contributes to poverty reduction, and this finding is also robust for the different poverty lines, with the poverty reduction magnitudes decreasing at higher poverty lines. These welfare improvements take place through a rise in yields and agricultural revenue, where adoption of improved maize seeds leads to a rise in agricultural yields of 13 per cent, and to a 23 per cent increase in the total value of agricultural production. In addition, a DH was run to further test that the increase in expenditure and reduction in poverty from improved maize seeds also take place through a rise in maize yields and value of improved maize production. These results corroborate the findings of other studies reviewed earlier, notably Becerril and Abdulai (2010), Khonje et al. (2015), and Mathenge, Smale and Olwande (2014). The results have different magnitudes but present similar direction across the different models.

Last, given that we observed results where state dependence is highly significant throughout all specifications, implying that the current adoption decision process is strongly influenced by past adoption, and that welfare returns and the extent of poverty reduction seem to be a function of the decision to adopt, we investigated the hypothesis of heterogeneous returns to adoption as in Suri (2011) through CRCs. We find that, when looking at outcomes in terms of total maize yields (in kilograms), the aggregate returns on yields are positive and statistically significant. However, this finding indicates that the returns are independent of the technology in question, e.g. they are uncorrelated with the decision to adopt improved seeds, and that there is no selection and heterogeneity across the different adoption history patterns. However, when we turn to poverty outcomes, we find that there is indeed endogenous selection (this was also present in the ESRM model where the aggregate return is positive, i.e. poverty headcount decreases) but that the individual returns are negative and significant, hence conditional on the adoption history, corroborating the heterogeneity hypothesis. These results indicate that farmers who initially adopted had the highest poverty reduction by switching from being an early adopter to a disadopter, possibly due to the occurrence of shocks (possibly price shocks), or unavailability of seeds in later periods, or inefficiencies in seed distribution systems – variables that we cannot test with the current dataset as they are not available in later waves. The highest poverty reduction gains were observed among those who exhibited a switching behaviour (mixed adopters and disadopters), possibly to counteract these unobservable shocks over the panel period. Therefore, significant policy implications for future technology dissemination can be drawn from this work.

During the three-year period analysed in this study (2009-2011), several shocks reduced the supply and demand for improved seeds, possibly explaining the heterogeneity of impacts among the different types of adopters. In 2010, the President suspended NAADS' operations for five months due to poor accountability of its funds and to cases of corruption. A government study estimated that the drought of 2010 led to losses of 7.5 per cent of GDP, equivalent to US$1.2 billion. The impact of the drought in the agriculture sector accounted for 77 per cent of this total. Maize was the second-most affected crop, after bananas.

Evidence from these data points to the fact that, regardless of the unequivocal findings that adopters benefit in terms of higher yields and higher poverty reduction, and that these benefits may increase over time, disadoption is a reality that seems to be a function of weak extension systems, liquidity constraints, lack of access to seeds locally, and vulnerability to climate change. All these factors are spatially heterogeneous, as noted by the regional coefficients. However, even with state dependence and weak agriculture extension services, the equilibrium adoption rate is most likely to be low. Strengthening of extension services can be highly effective in increasing adoption, coupled with state dependence. With state dependence, the value of adoption for farmers increases with the level of adoption. Adequate extension services could create positive feedbacks, leading to much higher adoption rates and significant welfare improvements. As suggested by Cowan and Gunby (1996), extension resources should possibly be first geographically located all in one area and subsequently expanded to other regions, once the former are strongly established and are functional. Moreover, it would be ideal to tailor extension advice to local climatic conditions, given the increase in intensity and frequency of weather shocks.

Another key finding from this work is that the heterogeneity of the adoption decision process is only a significant factor for poverty reduction – namely that there are statistically significant differences in the individual returns to poverty reduction that are conditional on the history of adoption. For example, those who switch in and out of the technology seem to exhibit higher returns to poverty reduction. These findings could be further tested with longer panels with higher adoption rates.

Past investments in research and advisory services in Uganda have yielded significant benefits, but the increasing demands for NAADS to provide more inputs at the expense of quality advisory services may negate those earlier benefits.

The collaboration between the National Agricultural Research Organisation (NARO) and NAADS has been successful in some locations, but a formal mechanism for collaboration is still missing. NARO receives poor or no feedback about farmers' demands, which constrains the ability to refine technologies. NARO's priority-setting does not often reflect crucial short-term priorities for enterprise development and marketing. As a result, there is little match between NARO and NAADS priorities at the zonal level and, thus, the overall efficiency of public spending in this sector is low.

The provision of inputs by NAADS should be limited to demonstrations to encourage wide adoption of promoted technologies. If the government wants to subsidize inputs on a large scale, then the subsidy would need to be delivered through alternative channels, for example, through local government. The provision of inputs through NAADS, if scaled up from the current small demonstration packages, would be anti-poor and detrimental to the quality of advisory services.

References

Adato, M. and Meinzen-Dick, R. S. 2007. *Agricultural Research, Livelihoods, and Poverty: Studies of economic and social impacts in six countries*. Baltimore, USA, Johns Hopkins University Press.

Adelman, I. 1975. Growth, income distribution and equity-oriented development strategies. *World Development*, 3(2-3): 67-76.

Alston, J., Wyatt, T. J., Pardey, P., Marra, M. and Chan-Kang, C. 2000. A meta-analysis of rates of return to agricultural R & D: ex pede Herculem? (No. 113). International Food Policy Research Institute (IFPRI).

Asfaw, S., Kassie, M., Simtowe, F. and Lipper, L. 2012a. Poverty reduction effects of agricultural technology adoption: a micro-evidence from rural Tanzania. *Journal of Development Studies*, 48: 1288-1305.

Asfaw, S., Shiferaw B., Simtowe, F. and Lipper, L. 2012b. Impact of modern agricultural technologies on smallholder welfare: evidence from Tanzania and Ethiopia. *Food Policy*, 37: 283-295.

Bandiera, O. and Rasul, I. 2003. Complementarities, social networks and technology adoption in northern Mozambique. London School of Economics. Unpublished manuscript.

Becerril, J. and Abdulai, A. 2010. The impact of improved maize varieties on poverty in Mexico: a propensity score-matching approach. *World Development*, 38(7): 1024-1035.

Benin, S., Nkonya, E., Okecho, G., Pender, J. L., Nahdy, S., Mugarura, S. and Kayobyo, G. 2011. Impact of Uganda's National Agricultural Advisory Services Program. International Food Policy Research Institute (IFPRI) research monograph, www.ifpri.org/publication/impact-uganda per centE2 per cent80 per cent99s-national-agricultural-advisory-services-program

Besley, T. and Case, A. 1993. Modeling technology adoption in developing countries. *American Economic Review*, 83(2): 396-402.

Bezu, S., Kassie, G. T., Shiferaw, B. and Ricker-Gilbert, J. 2014. Impact of improved maize adoption on welfare of farm households in Malawi: a panel data analysis. *World Development*, 59: 120-131.

Chamberlain, G. 1982. Multivariate Regression Models for Panel Data. *Journal of Econometrics*, 18: 5-46.

Chamberlain, G. 1984. Panel data. In: Z. Griliches and M. Intriligator, eds. *Handbook of Econometrics*, Vol. 2, pp. 1247-1318. Elsevier.

Conley, T. G. and Udry, C. R. 2010. Learning about a new technology: pineapple in Ghana. *The American Economic Review*, 100(1): 35-69.

Cowan, R. and Gunby, P. 1996. Sprayed to death: path dependence, lock-in and pest control strategies. *The Economic Journal*, 106(436): 521-542.

Cragg, J. G. 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica: Journal of the Econometric Society*, 39(5): 829-844.

Cummings, R. J. 1975. The Puebla Project. Paper prepared for meeting on social science research in rural development, Rockefeller Foundation, April 1975.

Cunguara, B. and Darnhofer, I. 2011. Assessing the impact of improved agricultural technologies on household income in rural Mozambique. *Food Policy*, 36(3): 378-390.

de Janvry, A. 2010. Agriculture for development: new paradigm and options for success. *Agricultural Economics*, 41(S1): 17-36.

de Janvry, A. and Sadoulet, E. 2002. World poverty and the role of agricultural technology: direct and indirect effects. *Journal of Development Studies*, 38(4): 1–26.

de Janvry, A. and Sadoulet, E. 2010. Agricultural growth and poverty reduction: additional evidence. *World Bank Research Observer*, 25: 1-20.

Deaton, A. and Zaidi, S. 2002. *Guidelines for Constructing Consumption Aggregates for Welfare Analysis*. LSMS Working Paper No. 135. Washington, DC, World Bank.

Di Falco, S., Veronesi, M. and Yesuf, M. 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3): 829–846.

Feder, G., Just, R. E. and Zilberman, D. 1985. Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, 33(2), 255-298.

Foster, A. D. and Rosenzweig, M. R. 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy*, 103(6): 1176-1209.

Griliches, Z. 1957. Hybrid corn: an exploration in the economics of technological change. *Econometrica, Journal of the Econometric Society*, 25(4): 501-522.

Heckman, J. J. 1979. Sample Selection Bias as a Specification Error. *Econometrica*, 47(1): 153-161.

Haggblade, S., Hammer, J. and Hazell, P. 1991. Modeling agricultural growth multipliers. *American Journal of Agricultural Economics*, 73(2): 361-374.

Imbens, G. and Wooldridge, J. 2008. *Recent Developments in the Econometrics of Program Evaluation*. Discussion Paper No. 3640. Institute for the Study of Labor (IZA), Bonn, Germany.

International Fund for Agricultural Development (IFAD). 2013. *Republic of Uganda Country Strategic Opportunities*. Rome.

Kasirye, I. 2013. *Constraint to Agricultural Technology Adoption in Uganda: Evidence from the 2005/2006-2009/2010 Uganda National Panel Survey*. Economic Policy Research Centre (EPRC) series 102, http://ageconsearch.umn.edu/bitstream/151979/2/series102.pdf

Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R. and Mulugeta, E. 2008. Estimating returns to soil conservation adoption in the northern Ethiopian highlands. *Agricultural Economics*, 38(2): 213-232.

Kassie, M., Shiferaw, B. and Muricho, G. 2011. Agricultural technology, crop income, and poverty alleviation in Uganda. *World Development*, 39(10): 1784-1795.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F. and Mekuria, M. 2013. Adoption of interrelated sustainable agricultural practices in smallholder systems: evidence from rural Tanzania. *Technological Forecasting and Social Change*, 80(3): 525–540.

Khonje, M., Manda, J., Alene, A. D. and Kassie, M. 2015. Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World Development*, 66: 695-706.

Kijima, Y., Otsuka, K. and Sserunkuuma, D. 2011. An inquiry into constraints on a green revolution in Sub-Saharan Africa: the case of NERICA rice in Uganda. *World Development*, 39(1): 77-86.

Kikulwe, E. M., Kabunga, N. and Qaim, M. 2012. Impact of Tissue Culture Banana Technology in Kenya: A difference-in-difference estimation approach. Poverty, Equity and Growth Discussion Paper No. 117. Courant Research Centre, www2.vwl.wiso.uni-goettingen.de/courant-papers/CRC-PEG_DP_117.pdf

Kjær, A. M. and Joughin, J. 2012. The reversal of agricultural reform in Uganda: ownership and values. *Policy and Society*, 31(4): 319-330.

Lambrecht, I., Vanlauwe, B., Merckx, R. and Maertens, M. 2014. Understanding the process of agricultural technology adoption: mineral fertilizer in eastern DR Congo. *World Development*, 59: 132-146.

Lewbel, A. 2007. Estimation of average treatment effects with misclassification. *Econometrica*, 75(2): 537-551.

Mathenge, M. K., Smale, M. and Olwande, J. 2014. The impacts of hybrid maize seed on the welfare of farming households in Kenya. *Food Policy*, 44: 262-271.

Mendola, M. 2007. Agricultural technology adoption and poverty reduction: a propensity-score matching analysis for rural Bangladesh. *Food Policy*, 32(3): 372-393.

Moser, C. M. and Barrett, C. B. 2003. The disappointing adoption dynamics of a yield-increasing, low external-input technology: the case of SRI in Madagascar. *Agricultural Systems*, 76(3): 1085-1100.

Mundlak, Y. 1978. On the pooling of time series and cross-section data. *Econometrica*, 46: 69-85.

Munshi, K. 2004. Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution. *Journal of Development Economics*, 73(1): 185-213.

Office of the President (OPM). 2012. The 2010-2011 *Integrated Rainfall Variability Impacts, Needs Assessment and Drought Risk Management Strategy*. Department of Disaster Management, Office of the Prime Minister, Government of Uganda.

Oster, E. and Thornton, R. 2012. Determinants of technology adoption: peer effects in menstrual cup take-up. *Journal of the European Economic Association*, 10(6): 1263–1293.

Papke, L. E. and Wooldridge, J. M. 2008. Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics*, 145(1): 121-133.

Rivers, D. and Vuong, Q. H. 1988. Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics*, 39(3): 347-366.

Shiferaw, B., Kassie, M., Jaleta, M. and Yirga, C. 2014. Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, 44: 272-284.

Smale, M. and Mason, N. 2014. Hybrid seed and the economic well-being of smallholder maize farmers in Zambia. *Journal of Development Studies*, 50(5): 680-695.

Smith, R. J. and Blundell, R. W. 1986. An exogeneity test for a simultaneous equation Tobit model with an application to labor supply. E*conometrica: Journal of the Econometric Society*, 54(3): 679-685.

Sserunkuuma, D. 2005. The adoption and impact of improved maize and land management technologies in Uganda. *Journal of Agricultural and Development Economics*, 2: 67-84.

Stewart, R., Langer, L., Rebelo Da Silva, N., Muchiri, E., Zaranyika, H., Erasmus, Y., Randall, N., Rafferty, S., Korth, M., Madinga, N. and de Wet, T. 2015. *The Effects of Training, Innovation and New Technology on African Smallholder Farmers' Economic Outcomes and Food Security: A systematic review*. 3ie Grantee Final Review. London, International Initiative for Impact Evaluation (3ie).

Suri, T. 2011. Selection and comparative advantage in technology adoption. *Econometrica*, 79(1): 159-209.

Tanellari, E., Kostandini, G., Bonabana-Wabbi, J. and Murray, A. 2014. Gender impacts on adoption of new technologies: the case of improved groundnut varieties in Uganda. *African Journal of Agriculture and Resource Economics*, 9(4): 300-308.

Thirtle, C. and Piesse, J. 2003. The impact of research-led agricultural productivity growth on poverty reduction in Africa, Asia and Latin America. *World Development*, 31(12): 1959-1975.

Uganda Bureau of Statistics. 2005. *Uganda National Household Survey 2005/06 – Socio-economic Report, December 2006*. Kampala, Uganda.

Uganda Bureau of Statistics. 2011. *Uganda National Household Survey 2011-12: Wave III Report, November 2013*. Kampala, Uganda.

Vella, F. 1993. A simple estimator for simultaneous models with censored endogenous regressors. *Institute of Social and Economic Research Association*, 34(2): 441-457.

Verkaart, S., Munyua, B. G., Mausch, K. and Michler, J. D. 2017. Welfare impacts of improved chickpea adoption: a pathway for rural development in Ethiopia? *Food Policy*, 66: 50-61.

Wooldridge, J. M. 2005. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, 20: 39-54.

Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, USA, MIT Press.

World Bank. 2014. *World Development Indicators*. GNI per capita, Atlas method, http://data.worldbank.org/indicator/NY.GDP.PCAP.CN and http://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD

Appendix 1: Correlated random coefficient model

Log of total maize yields in kilograms

Table A1.1 Explanation of transitions across adoption of improved maize varieties for the sample period

	Adoption choice in each year of the sample		
Type of adopter	2009	2010	2011
Always adopter	1	1	1
Early adopter	0	1	1
Late adopter	0	0	1
Mixed adopter	1	0	1
Mixed disadopter	0	1	0
Late disadopter	1	1	0
Early disadopter	1	0	0
Never disadopter	0	0	0

Note: The value 1 indicates that adoption took place and the value 0 means non-adoption.

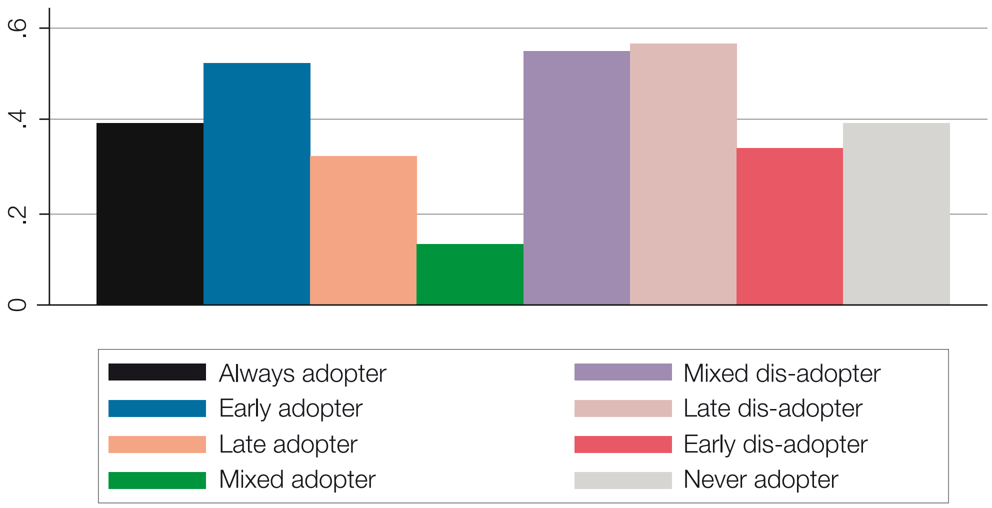
Table A1.2 CRC results with the log of total maize yields in kilograms as the outcome variable

	Estimate	Standard error	P value
Interaction I1	0.14	0.24	0.56
Interaction I2	-0.42	0.33	0.21
Interaction I3	0.17	0.23	0.47
Interaction I4	-0.18	0.43	0.68
Interaction I5	0.37	0.38	0.33
Interaction I6	-0.09	0.62	0.90
Interaction I7	0.00	0.82	1.00
Aggregate return	0.39**	0.2	0.05
Individual's comparative advantage in adoption	-0.38	0.41	0.36

* p < 0.10, ** p < 0.05, *** p<0.01.

Figure A1.1 shows that greatest impacts are for the early adopter, the mixed disadopter and the late disadopter. Table A1.1 provides an explanation of the different types of adopters. In Table A1.2, the aggregate return to improved maize seeds is statistically significant. The coefficient on the individual's comparative advantage in adoption is not statistically significant, indicating that although the aggregate returns on yields are positive, the heterogeneity found is not statistically significant.

Figure A1.1 Distribution of returns to adoption to the log of total maize yields in kilograms



Poverty headcount (medianPL)

Table A1.3 CRC results with the poverty headcount (medianPL) as the outcome variable

	Estimate	Standard error	P value
Interaction I1	-0.10	0.05	0.03
Interaction I2	0.00	0.07	0.96
Interaction I3	-0.03	0.05	0.50
Interaction I4	-0.03	0.10	0.76
Interaction I5	0.1	0.1	0.32
Interaction I6	-0.32	0.18	0.08
Interaction I7	0.35	0.25	0.17
Aggregate return	-0.09***	0.04	0.01
Individual's comparative advantage in adoption	-1.47***	0.38	0.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1.2 Distribution of returns to adoption to the poverty headcount (medianPL)

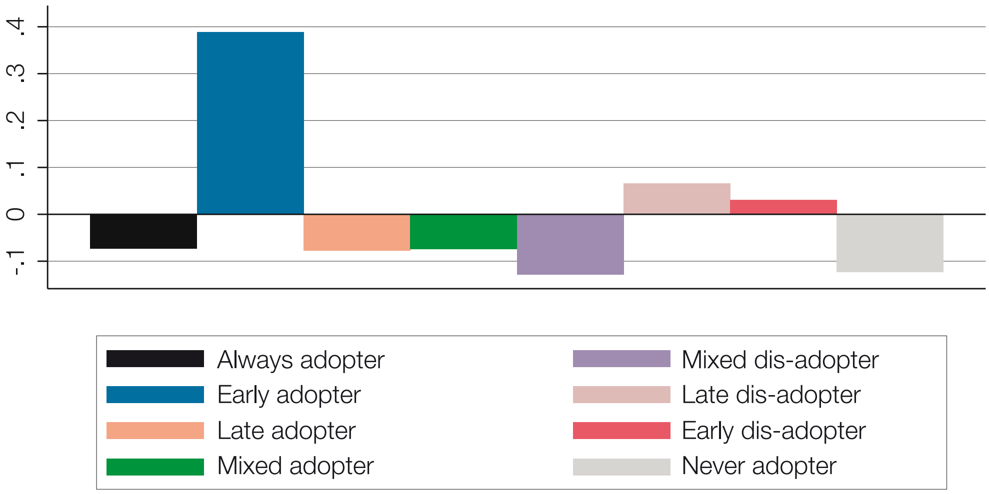


Figure A1.2 shows that the aggregate returns to poverty are statistically significant. We display this poverty line (PL) as results are robust to the choice of PL. Being an early adopter is detrimental to poverty reduction, worse than never adopting. In Table A1.3, the coefficient on the individual's comparative advantage in adoption is statistically significant, indicating that there is heterogeneity in returns to poverty that are conditional on the adoption decision history.

Appendix 2: Control function estimation

Table A2.1 Estimation of the impact of adoption on outcome variables, control function (CF) estimation

		CF model	Mean of non-adopters in the CF model	No.
1	Log of daily constant total expenditure in US$ PPP per adult equivalent	0.05 (0.06)	1.05	2,361
2	Log of daily constant non-food expenditure in US$ PPP per adult equivalent	0.02 (0.06)	0.68	2,361
3	Log of daily constant food expenditure in US$ PPP per adult equivalent	0.08* (0.04)	0.63	2,361
4	Poverty headcount (medianPL)	0.02* (0.01)	0.50	2,361
5	Poverty headcount (US$2 PPP PL)	-0.04*** (0.01)	0.56	2,361
6	Poverty headcount (60thPL)	-0.00 (0.01)	0.62	2,361
7	Log of total agricultural yields in kilograms	-0.16 (0.24)	6.31	1,281
8	Log of total value from agricultural production in constant Ugandan shillings	-0.03 (0.21)	14.19	1,281

Notes:
a. Clustered standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
b. LSMS Uganda, years 2009, 2010 and 2011.
c. Source: authors' estimations.

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IFAD

International Fund for Agricultural Development
Via Paolo di Dono, 44 - 00142 Rome, Italy
Tel: +39 06 54591 - Fax: +39 06 5043463
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www.ifad.org
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