Poor farmers: Agricultural innovation and poverty reduction in Ethiopia and Kenya

Simone Verkaart

Poor farmers

Agricultural innovation and poverty reduction in Ethiopia and Kenya

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INVITATION

You are cordially invited to
attend the public defence
of my PhD thesis entitled:

Poor farmers
Agricultural innovation
and poverty reduction
in Ethiopia and Kenya

on Friday 1 June 2018,
at 11:00 PM in the Aula of
Wageningen University,
Generaal Foulkesweg 1A,
Wageningen

Simone Verkaart
simoneverkaart@gmail.com

Paranymphs
Bram Frouws
bram.frouws@gmail.com

Kik Verkaart
kikpsych@hotmail.com

Propositions

1. Agricultural technology transfer is effective only when focused on farmers who aspire and are able to increase their farming income.
   (this thesis)

2. The focus of agricultural research for development (AR4D) on crop yields is misguided, because productivity without profitability cannot reduce poverty.
   (this thesis)

3. Whenever possible, impact assessment should be based on experimental research.

4. A crop breeder selecting improved varieties for upscaling is equal to a butcher testing the quality of his own meat.

5. Reducing poverty without building resilience is not sustainable.

6. Without world peace it is not possible to end poverty and hunger.

Propositions belonging to the thesis, entitled

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Simone Verkaart
Wageningen, 1 June 2018

Poor farmers

Agricultural innovation and poverty reduction in Ethiopia and Kenya

Simone Verkaart

Thesis committee

Promotors
Prof. Dr E.W. Bulte
Professor of Development Economics
Wageningen University & Research

Prof. Dr K.E. Giller
Professor of Plant Production Systems
Wageningen University & Research

Other members
Prof. Dr J.H.H. Wesseler, Wageningen University & Research
Prof. Dr M. Maertens, KU Leuven, Belgium
Dr M. Kassie, International Centre of Insect Physiology and Ecology, Nairobi, Kenya
Dr D. Glover, Institute of Development Studies, Brighton, United Kingdom

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Chapter 1
General introduction

1

1.1 Background

Agricultural development is often portrayed as an important precondition for meeting international development goals. The 2008 World Development Report stated that agriculture is an important pathway for the rural poor to move out of poverty (World Bank, 2007). Commitment to rural development was renewed with the adoption of Sustainable Development Goal (SDG) 1 and 2, which respectively aim to end poverty and hunger by 2030 (United Nations, 2015). Achieving these goals will be a complex and difficult undertaking that demands a raft of policy measures for agriculture and poverty reduction (de Waal, 2015). In sub-Saharan Africa[1] reducing poverty and hunger have been overriding policy concerns for the past half century (Muyanga & Jayne, 2014). Agriculture underpins the livelihoods of over two-thirds of Africa's poor who depend primarily on rainfed production of staple crops (Burney & Naylor, 2012; Pretty et al., 2011). At the same time, the region remains the most food insecure region in the world (OECD/FAO, 2016). Boosting agricultural production in the face of a growing population is therefore one of the major challenges facing sub-Saharan Africa (Ricker-Gilbert et al., 2014). Thus, agricultural development is considered critical for sustained poverty reduction in many African countries (Dercon et al., 2009).

Agricultural innovations are often promoted as a pathway from poverty for rural households. It is generally agreed that agricultural innovation is a prerequisite for sustainable rural development in Africa (Glover et al., 2016). An important challenge in sub-Saharan Africa is to move from extensification, i.e., agricultural growth by expanding cultivated area, to intensification, i.e., increases in land productivity (Delaney et al., 2011). In short, African agriculture will have to be intensified (Pretty et al., 2011). Dzanku et al. (2015) indeed found that agricultural technology has considerable promise to increase yields and contribute to poverty reduction in sub-Saharan Africa. Other authors similarly noted that new technology holds considerable promise for improvements of African agriculture (Clark et al., 2013). Activities designed to address the vulnerability of the rural African poor therefore often aim to improve agricultural practices to increase productivity, efficiency and ultimately income (Parvan, 2011). As a result, efforts to improve the productivity of smallholder farms are a core feature of development strategies promoted by African governments and international development agencies (Larson et al., 2014). In sum, agricultural innovations are seen as a key element in promoting African rural development.

The adoption of agricultural innovations in sub-Saharan Africa has proved challenging. The low adoption of agricultural technologies is well documented and a widely cited reason for low agricultural productivity in sub-Saharan Africa (Headey & Jayne, 2014; World Bank, 2015c). While crop productivity has risen globally over the last 40 years, it remained stagnant in Africa (Jayne & Muyanga, 2012). Moreover, yield gaps in African smallholder farming are among the largest in the world (Tittonell & Giller, 2013) and there has been limited success in sparking a so-called African Green Revolution (Otsuka & Kijima, 2010). Without

[1] The sub-Saharan African region is defined by the United Nations Statistical Division and is used to indicate all of Africa, except Northern Africa, with Sudan included in sub-Saharan Africa. Throughout this thesis I refer to sub-Saharan Africa whenever I use the term Africa.

attention to sustained agricultural productivity growth, small farms in Africa can become increasingly unviable economic units (Jayne et al., 2010). Collier and Dercon (2014) even argued that it might be time to think more seriously about larger scale agricultural development and migration out of agriculture by poor households. According to these authors, having the single most important sector of Africa's economies almost exclusively run by 'reluctant micro-entrepreneurs' is a recipe for continued divergence from global agricultural performance. They also argue, however, that there is a strong poverty-based case for trying to assist smallholders. A looming policy question is therefore whether agricultural policy should retain poverty reduction as a primary goal or whether it should focus on promoting efficiency and productivity and seek to achieve poverty reduction goals through some other means (Jayne et al., 2014). The future role of smallholder agricultural producers in global food production and food security is therefore deemed highly uncertain (Herrero et al., 2014).

Despite decades worth of research there is still much debate on the role of smallholder farmers in agricultural development. My aim is to contribute to this debate and the wider literature on agricultural research for development. I do this by exploring the various meanings behind the title 'poor farmers'. First, I explore agriculture's potential contribution to rural welfare by analysing the impact of agricultural innovations on poor farmers. Here, 'poor farmers' refers to the welfare status (poverty) of households and potential of agricultural innovations to improve this. Second, I study differences in the agricultural performance of smallholder farmers and assess whether and why some households may be poor farmers. Here, 'poor farmers' denotes the heterogeneity and possible agricultural underperformance of rural households compared to their neighbours. Third, I discuss how a suboptimal agricultural technology development and transfer process prevents many poor farmers to grow their way out of poverty. Here, 'poor farmers' refers to a sad reality wherein 'poor farmers' are unable to access and benefit from available agricultural innovations. Finally, the title was inspired by the book 'Poor Economics' (Banerjee & Duflo, 2012) and is a playful nod to the book, which is an ode to experimental impact assessment, while I applied quasi- or non-experimental methods in this thesis.

This thesis probes the extent that agricultural innovations can contribute to the welfare of smallholder farmers using two case studies. The first case study analyses the relationship between agricultural intensification, livelihood diversification and household aspirations using cross-section data collected in eastern Kenya. The second case study explores the determinants of improved chickpea adoption and the impact of adoption on household welfare using three rounds of panel data from the Shewa region in Ethiopia. The two case studies resulted in five papers presented as chapters in this thesis, with each exploring a separate topic. The chapters are connected by their focus on agricultural technology adoption and its implication for smallholder farmer welfare. The remainder of this chapter provides an overview of the key concepts and debates in the literature, introduces the context of the two country cases, describes the objectives and research questions of the thesis, briefly introduces the methodologies used and presents a further outline of the thesis.

1.2 Definitions

The concepts of innovation and technology are often used interchangeably in the literature. For example, innovation has been defined as a technological factor that can change the production function (Feder & Umali, 1993) and as the development and application of new knowledge, materials, tools and practices (Glover et al., 2016). Similarly, agricultural technologies have been defined as discrete inputs – either goods or methods – with the purpose of controlling and managing animal or vegetative growth (Parvan, 2011). Examples of agricultural technologies or innovations are improved varieties, cropping techniques, optimal input use, prices and market information, more efficient methods of production management and improved storage facilities (Anderson & Feder, 2007). Often technologies are offered as a complementary package, e.g., high yielding varieties, fertiliser and agronomic practices (Feder et al., 1985). In this thesis I focus on the adoption of improved chickpea varieties (Ethiopia) as well as agricultural intensification at the farm level using an adoption index that captures a range of technologies (Kenya).

Technology adoption is a complex process, but this is rarely reflected in measurement. There have been calls to move beyond a 'black box' conception of adoption as a dichotomous linear process whereby inferior existing material is replaced by a discrete new technology (Glover et al., 2016). Farmers regularly and actively make decisions about technology adoption and dis-adoption (Sumberg et al., 2004). Before deciding whether to adopt or not, farmers seek information on the cost and value of the innovation from their own and other users' experiments (Marra et al., 2003). Moreover, for innovations that are ''divisible'' and can be adopted in a stepwise manner, like a new variety, the adoption decision involves a decision regarding the intensity of adoption (Marra et al., 2003). Where technologies are introduced in complementary packages, farmers face distinct technological options as components could be adopted independently (Feder et al., 1985). Adoption also generally implicates the reallocation of resources, which can induce substitution by diverting land, labour, inputs and investments away from existing activities (Bevan et al., 1990). Finally, it is possible to distinguish between adoption by individual farmers and adoption at the aggregated regional or national level, with the latter often referred to as diffusion (Rogers, 1962). I study adoption at the farm level, capture its intensity and study movements in and out of adoption.

Technology transfer interventions aim to provide farmers with access to technologies. Clark et al. (2013) described technology transfer as a model whereby science conducted by specialised organisations, like the CGIAR,[2] produces generic knowledge that is then transferred to other bodies, notably National Agricultural Research Systems (NARS), until ultimately it receives expression in the fields of smallholder farmers. The term technology transfer has invoked hostility by conveying images of top-down blue-print approaches to development (Sumberg et al., 2012). Sumberg (2005) dubbed this a 'populist' critique, which sees agricultural research for development as being elitist, reductionist, top-down and supply driven. Some authors indeed suggested that 'conventional' technology transfer failed to

[2] Formerly the Consultative Group for International Agricultural Research.

promote adoption because of its top-down linear design (Pamuk et al., 2014). More participatory demand-driven technology transfer approaches, however, often place additional burdens on resource poor farmers who face competing demands on their time due to their increasingly diversified livelihoods (Sumberg et al., 2004). An unresolved issue in the literature is thus how to best provide agricultural innovations to farmers who are able and keen to adopt them. For the purpose of this thesis, I understand technology transfer as processes, whether participative or not, whereby farmers gain access to new or improved technology.

Smallholder farmers have specific features that are important when studying adoption and its impact on household welfare. Smallholders are most commonly defined as households that operate two hectare or less, depend predominantly on family labour and are resource poor (Stewart et al., 2014). In addition, smallholders produce goods for consumption while cash constraints are relaxed primarily through farm sales of surplus products and off-farm income (Smale & Mason, 2014). Thereby households are simultaneously involved in both production and consumption decisions and the assumption of separability between these decisions is unlikely to hold. Household endowments of natural, human, financial, physical and social capital constitute the resource constraints based on which well-being is maximized (Asfaw et al., 2012). Accordingly, adoption should be analysed using a non-separable model of the farm household, in which family members organize their labour to maximize utility over consumption goods and leisure in an economic environment with market failures (de Janvry et al., 1991).

This thesis analyses the relation between technology adoption and household welfare in relation to rural development. The concept of household welfare encompasses many dimensions (Bourguignon & Chakravarty, 2003; Sen, 1999). However, to focus the analysis I operationalized welfare as household income and poverty. Specifically, I estimated net household income using detailed data collected on crop and livestock production as well as off-farm income. Though household expenditure data is often used to estimate income and poverty, the focus on agricultural technology adoption and income diversification favoured the use of income. Net income was used to estimate whether households were above or below the international poverty line expressed in per capita per day terms.

Depending on the round of the International Comparison Program (ICP) used, the poverty line has been set at (Kakwani & Son, 2016): \$1 (1990 PPP), \$1.25 (2005 PPP) and \$1.90 (2011 PPP). Though not without controversy (Deaton, 2010; Klasen et al., 2016), the poverty line's prominence within the millennium and sustainable development goals has made it the standard used by the international development community for measuring extreme poverty in the world. Moreover, it is derived from the poverty lines of the poorest countries and thus expresses poverty according to the standards of these countries (Ravallion et al., 2009). Finally, operationalizing welfare as both income and poverty forestalls criticism that the poverty line considers only a specific threshold.

1.3 Technology adoption and poverty reduction

Despite an extensive body of research there is much uncertainty on the relationship between agricultural innovation and rural household welfare. Indeed, evidence on the relation of technology adoption and poverty reduction in sub-Saharan Africa has remained thin and mixed (Cunguara & Darnhofer, 2011; Kassie et al., 2011). In fact, systematic reviews commissioned by the International Initiative for Impact Evaluation (3ie) found insufficient evidence to draw conclusions on the impact of technology transfer on agricultural productivity (Loevinsohn et al., 2013) or smallholder wealth and food security (Stewart et al., 2015). Similarly, there is inconclusive evidence on the impacts of capacity strengthening of agricultural research systems (Posthumus et al., 2012), smallholder innovation grants (Ton et al., 2015) and conservation agriculture (Corbeels et al., 2014; Giller et al., 2015; Nkala et al., 2011). At the same time, there is increasing pressure to demonstrate impact, success and 'value for money' of agricultural research (Sumberg et al., 2012). Indeed, agricultural research and technology development compete for policy attention and investment with other high-profile sectors such as health and education (Glover et al., 2016). Given that development resources are scarce, efforts should be made to identify interventions that will generate the greatest payoffs (Ariga & Jayne, 2011). Hence, it seems clear that agriculture's contribution to poverty reduction requires further investigation.

Many studies have tried to explain technology adoption. A longstanding and extensive body of research is concerned with the determinants of (agricultural) technology adoption (e.g., Feder et al., 1985; Feder & Umali, 1993; Foster & Rosenzweig, 2010; Jack, 2011; Lee, 2005; Sunding & Zilberman, 2001). Nonetheless, there is said to be little coherent understanding of technological change in smallholder African agriculture, let alone the dynamics of these processes (Glover et al., 2016). Inevitably, adoption decisions are influenced by many factors (Anderson & Feder, 2007). In accordance with the seminal study by Feder et al. (1985) adoption is often explained in relation to farm size (Headey & Jayne, 2014; Josephson et al., 2014), risk preferences (Dercon & Christiaensen, 2011; Wossen et al., 2015), human capital (Liu & Yamauchi, 2014), labour availability (Jayne et al., 2014; Ndlovu et al., 2014), credit constraints (Holden & Lunduka, 2013), land tenure (Beekman & Bulte, 2012; Jin & Jayne, 2013; Melesse & Bulte, 2015), access to input and output markets (Jack, 2011; Jayne et al., 2010) or a combination of the above (Wakeyo & Gardebroek, 2013). A particularly major research topic is why agricultural innovations that seem beneficial are under adopted (Zilberman et al., 2012). Often the notion of constraint is used to analyse factors that are thought to inhibit farmers from adopting. Sumberg (2005), however, questioned how useful it is to suggest that innovations are under-adopted because well-known pre-requisite conditions are absent. He therefore advocates for more attention to the benefits of technology and the goodness-of-fit with intended users in a specific context.

Agricultural technology adoption is the result of rural household decision-making processes in a specific context. The debate on the role of small farms in poverty alleviation may have remained unresolved partly because key relationships are context dependent (Gebremedhin et al., 2009). It is too simplistic to assume that promoting agricultural technologies will automatically boost productivity, improve livelihoods and alleviate poverty (Tittonell, 2007). The potential effect of technology transfer depends on whether farmers adopt and, if they do, whether they adopt the technologies in an ideal combination and for the prescribed length of time needed to produce results (Parvan, 2011). It has been noted that the large diversity within and among smallholder farming systems will affect the uptake of technologies (Franke et al., 2014; Frelat et al., 2016). To structure the analysis, factors that influence the adoption process can be broadly divided into characteristics of the technology, the intended users and the context in which adoption takes place (Biagini et al., 2014). Ultimately the interplay among these three aspects needs to be addressed to more fully understand adoption decisions (Foster & Rosenzweig, 2010). Hence, it is important to study where, when and for whom specific agricultural innovations can improve household welfare.

1.3.1 Technology characteristics and returns

The characteristics of agricultural innovations influence their adoption. In order to be adopted an innovation should address an important demand and/or deliver desired benefits to its intended users (Sumberg, 2005). Indeed, the relative advantage offered by a technology has been indicated as one of the best predictors for an innovation's rate of adoption (Rogers, 1962). Adoption decisions are therefore often assumed to be the outcome of optimizing expected utility (Feder et al., 1985). Agricultural technologies can offer various additional benefits: higher yields, lower risk, better quality, lower costs and/or reduced externalities. The bandwidth of returns and associated risk are also important determinants for adoption (Marra et al., 2003). For example, poor farm households in rainfed and risky production environments have been found reluctant to adopt new farm technologies that could improve production because these technologies involved large downside risks in terms of crop failure (Ogada et al., 2010). Others suggested that new technology should reduce the negative externalities of agriculture (Pretty, 2008; Pretty et al., 2011). Accordingly, 'sustainable intensification' has been defined as the application of technology that can increase food production from existing farm land, places less pressure on the environment and does not undermine the capacity to continue producing food in the future (Garnett et al., 2013). Despite its desirability, sustainability is not necessarily an immediate concern for smallholders as their adoption decisions are determined largely by short-term profitability (Vanlauwe et al., 2014). Environmentally sustainable technologies will thus have to generate positive economic benefits if they are to achieve wide adoption (Lee, 2005).

Net returns or profits are important indicators for the attractiveness of a technology. When calculating whether or not a technology is worthwhile, the labour and capital investments that are necessary to enable adoption of the technology need to be taken into consideration (Jack, 2011). Profits or net returns account for both changes in revenues from increased outputs or prices as well as changes in expenses from input adjustment (de Janvry et al., 2011). It is thus surprising that few studies analyse the profits or net returns to technologies that are said to be under adopted (Foster & Rosenzweig, 2010). A notable exception is the study by Suri (2011), who found that returns and costs of technologies are heterogeneous and that farmers who face lower net returns will not adopt a technology. Another example is a study on the returns to chemical fertiliser by Duflo et al. (2008), though this does not account for family labour. Harris and Orr (2014) reviewed studies reporting net returns, partly from on-station trials, and found that returns to adoption were considerable but often insufficient to lift smallholders above the poverty line. Where farming contributes only a small portion of household income or if farm sizes are small, even adopting profitable technologies will have only a marginal effect on income (de Janvry et al., 2011). This signifies the importance of estimating the impact of technology adoption on household income or welfare in determining its attractiveness. It further shows that productivity gain is a necessary, but not sufficient, condition to increase income and attract farmers to adopt agricultural innovations.

Adoption is dependent on technology characteristics that influence learning about its relative attractiveness. Ghadim and Pannell (1999) conceptualized technology adoption as a multi-stage decision process involving information acquisition and learning-by-doing by growers on the attractiveness of an innovation. Initially, potential adopters have a cautious approach towards adoption, but through experimentation they improve their knowledge on the best use of the innovation and reduce their uncertainty about its potential benefits (Marra et al., 2003). Rogers (1962) indicated that the complexity, trialability and observability of results influence adoption. Complexity can be defined as the degree to which an innovation is difficult or simple to understand and use. Trialability concerns the degree to which an innovation may be experimented with on a limited basis. Finally, observability relates to the visibility of an innovation's results as well as the ease with which it can be communicated to others. These characteristics determine the ease of learning about a new technology and its returns in settings where a technology is newly introduced (Foster & Rosenzweig, 2010).

Access to a technology is an important pre-condition but common constraint to adoption. Awareness of a technology and its characteristics is the first step leading to adoption (Lee, 2005). If potential users are not exposed to an innovation, expectations of adoption will be misplaced (Sumberg, 2005). Often farmers who could benefit from the adoption of agricultural technologies are unable to access them (Jack, 2011). For example, the adoption of improved varieties depends on the availability and accessibility of improved seeds (Asfaw et al., 2012). It is thus important that adoption is actually a choice that can be taken in the sense that technology is available, accessible and affordable (de Janvry et al., 2011; Poulton & Macartney, 2012). It has also been proposed that smallholder success is often not determined by the adoption of a technology per se, but whether a household has internalized a learning style that facilitates the exploration, evaluation and adaptation of technological alternatives in the broader context of managing resources and earning a livelihood (Lee, 2005). Innovations can be provided through technology transfer interventions, but their affordability and accessibility depend on the intended users and the context in which they operate.

1.3.2 Technology users and decision-makers

Characteristics of the users of technology affect adoption. Household characteristics such as land ownership, labour availability, education and demographics, such age, gender and household size, may differ widely and can influence adoption decisions in various ways

(Wakeyo & Gardebroek, 2013). If there are scale effects associated with adoption or the technology is complex, the size of the land owned and education of the farmer may affect adoption. Indeed, some major determinants of adoption include (Foster & Rosenzweig, 2010): (i) adoption and schooling are positively correlated, net of wealth; (ii) larger and wealthier farmers are more likely to adopt new technologies than poorer households; and (iii) the adoption by an individual farmer is positively correlated with the extent of prior adoption by his or her neighbours. Farmer age and experience are often expected to be positively associated with adoption, but because they are also associated with increased aversion to risk the relationship need not be positive or significant (Lee, 2005). A systematic exploration of the needs and opportunities of the diversity of farmers in a given region is important to understand adoption decisions (Giller et al., 2015). Even so, there is often too little attention for the fact that successful adoption is dependent on people and their aspirations, skills, and so on (Sumberg, 2005).

Adoption decisions are affected by rural livelihood strategies. Innovations need to be compatible with the other farm and non-farm activities of potential users (Sumberg, 2005). Rural households and individual decision-makers have diverse livelihood strategies and long-term aspirations (Tittonell, 2007). Gone are the days when rural populations were simply assumed to be farmers (Freeman & Ellis, 2005; Sumberg et al., 2004). Instead, diversification is the norm (Barrett et al., 2001). Diversification can be defined as a process by which households construct a diverse portfolio of income generating activities to improve their living standards (Ellis, 1998). Many farmers work part time outside agriculture but keep a foot in agriculture to avoid being too dependent on their non-agricultural jobs (Banerjee & Duflo, 2007). By contrast, some households aim to step completely out of agriculture by migrating to cities or specializing into non-farm rural activities (Dorward et al., 2009). Where the share of farming in household income declines, the expected benefits to adoption need to increase in order for a technology to remain attractive (Sumberg et al., 2004). In contexts where households grow a wide diversity of crops or are dependent on other income sources, households may be less interested in adopting technology (Mason & Smale, 2013). These dynamics should be taken into account when targeting technological innovations and rural development efforts (Tittonell et al., 2010). This highlights the importance of distinguishing between rural and farm households, and the importance of off-farm income when studying adoption.

Rogers (1962) indicated that technologies need to be compatible with the existing preferences and needs of adopters. For example, adoption plateaus for modern maize varieties in Malawi have been partly attributed to the favourable taste of local varieties compared to hybrids (Lunduka et al., 2012). Other preferences are related to specific processing and storage requirements (ibid). Similarly, farmers may vary in their risk preferences and their perceptions of an innovation's riskiness (Marra et al., 2003). Other studies explore the role of learning (e.g., Bandiera & Rasul, 2006; BenYishay & Mobarak, 2014; Conley & Udry, 2001; Conley & Udry, 2010) or social capital in agricultural technology adoption (van Rijn et al., 2012a; Wossen et al., 2015). Behavioural research has advanced our understanding of the psychological, social and cultural influences on decision making and human behaviour

(World Bank, 2015c). Given the complexity of the adoption process and scarcity of studies capturing net returns, however, it may be that the resolution to some of the puzzles in the technology adoption literature lies in careful measurements of net returns rather than taking significant steps away from the standard economic paradigm (Foster & Rosenzweig, 2010). Indeed, the apparent unwillingness of smallholder farmer to innovate can be rational where there are serious disincentives to adopt (Dethier & Effenberger, 2012; Schultz, 1964).

Small farmers face particularly pressing constraints in relation to technology adoption. Jayne and Muyanga (2012) stated that many farms in Africa are becoming too small to generate meaningful production surpluses. Over 80% of farms in sub-Saharan Africa are now under two hectares (ha) (Lowder et al., 2014; Nagayets, 2005). In addition, 20 percent of Africa's rural land contains 80 percent of its rural population (Jayne et al., 2014). Other authors identified asset thresholds that divide food secure households with larger and higher quality lands from food insecure ones with smaller degraded farms (Stephens et al., 2012). At the same time, smallholders in sub-Saharan Africa have been found to be more productive, with yields falling as the scale of production rises (Carletto et al., 2013; Larson et al., 2014). However, yield is not necessarily the relevant variable to assess the efficiency of agriculture or its contribution to poverty reduction, where value added or net returns to land and labour has been said to be more relevant (Collier & Dercon, 2014). In relation to this it was already indicated that returns to crop production are often insufficient to lift smallholders above the poverty line (Harris & Orr, 2014). Where farm sizes continue to decline this may severely constrain the possibilities for intensification, leading to increased pressures for smallholders to exit farming (Thornton & Herrero, 2015).

1.3.3 The context of adoption

Adoption choices are conditioned on the context in which adoption takes place. For instance, adoption is dependent on the availability of complementary inputs and the demand for outputs (Sumberg, 2005). The functionality and structure of value chains as well access to markets, influence input and output prices (Chamberlin & Jayne, 2013). The modest scale of smallholders leads to relatively high unit transaction costs in accessing services such as capital, information, inputs and markets (Poulton et al., 2010). Moreover, the underdevelopment of rural African infrastructure hinders market access and leads to high transportation costs (Dethier & Effenberger, 2012). Given that inputs have to be paid up front and that returns to new technology are uncertain and sometimes riskier, access to credit and insurance also influences adoption (Foster & Rosenzweig, 2010). Tenure security has been identified as another important factor that can influence agricultural investment and productivity (Melesse & Bulte, 2015). However, markets for risk, credit or land are generally poorly functioning or even missing (Jack, 2011). These market imperfections erode the profitability of innovations for small farmers and can lower adoption. A key issue is thus how to integrate the smallholder farmer downstream into better market access and upstream into better input provision (Clark et al., 2013; Wiggins et al., 2010). This supports the argument by Frelat et al. (2016) that bridging yield gaps is important, but improving market access essential.

Farmers will not adopt technologies if they do not know how to use them. It is therefore important that the necessary institutional frameworks are in place to support adoption. Information about new technology comes from a variety of sources: farmers' own experience, neighbours' decisions and experiences and sources such as extension workers or the market (Jack, 2011). Agricultural extension has the potential to facilitate technology transfer and management and can also relay farmer needs back to innovators and policy makers to ensure that innovations meet local needs (Anderson & Feder, 2007). Farmer involvement with extension services and other sources of technical support are indeed consistently found to affect adoption (Lee, 2005). The adequate and timely access to relevant advice and training as well as the format by which such extension services are rendered is thus likely to influence adoption (Anderson & Feder, 2007). However, public extension services are often centralized, hierarchical, and unresponsive to the diverse needs of farmers (Dethier & Effenberger, 2012). Administrative and design failures of public extension have been associated with the scale and complexity of operations, difficulties inherent in tracing impact and profound problems of accountability (Anderson & Feder, 2007). It has therefore been proposed to put the private sector in charge of service provision to increase the accountability and quality of service provision as well as reduce the financial burden on the public sector (Dethier & Effenberger, 2012). However, the specific attributes of the extension process pose formidable challenges for management of effective service delivery, irrespective of whether the agent is public or private (Poulton & Macartney, 2012). Accordingly, there is considerable debate on the form that extension and wider technology transfer should take.

Agro-ecological conditions are important determinants of technology adoption. Characteristics such as soil quality, rainfall patterns, temperature and the farming system are important when studying adoption (Feder & Umali, 1993; Mason & Smale, 2013). Returns to technologies can differ across farmers depending on weather and soil and the variability of these factors (Foster & Rosenzweig, 2010). African agricultural systems are heterogeneous (Vanlauwe et al., 2014), which is a consequence of the high dependence on rainfed agriculture and microclimates that require specific farming practices (Jack, 2011). Moreover, in the future African agriculture will face increasing challenges related to climate change and variability (Thornton & Herrero, 2015). In addition, soils in densely populated areas have been continuously cultivated and are facing fertility constraints that make them less responsive to inorganic fertiliser (Muyanga & Jayne, 2014; Tittonell & Giller, 2013). Even within farms soil fertility may differ depending on the level of land use intensity and application of inputs (Vanlauwe et al., 2014). Accordingly, adoption of innovations has to be considered at the farm system level (Le Gal et al., 2011). Adopting a farm systems approach shows constraints to the adoption of conservation agriculture associated with increased labour-burdens and competition for crop-residues between soil-mulching and livestock feed (Giller et al., 2015). The diversity in agro-ecological and socio-economic conditions should thus be considered to better understand adoption.

1.4 A brief introduction of the study areas

This research focuses on the semi-arid and sub-humid tropics of East Africa, with a focus on Ethiopia and Kenya. As already indicated, smallholders operate and make decisions on technology adoption in vastly different biophysical and socio-economic contexts (Thornton & Herrero, 2015). It is therefore important to provide some more information on the country cases included in this thesis.

Table 1.1 provides development and agricultural indicators for Ethiopia, Kenya, sub-Saharan Africa and the world. Though the two countries performed worse than the global average on all indicators, most development indicators in Ethiopia and Kenya show steady improvements over the past fifteen years. There is limited information on recent poverty rates but life-expectancy rates are higher than the rest of sub-Saharan Africa. There are also some noteworthy differences between the two countries. For example, the 2015 Human Development Index (HDI) classified Kenya as the 145th country (out of 188) and it is as such the highest ranked low income country, while Ethiopia is classified as the 174th country (UNDP, 2015). Ethiopia, started out with very low primary education enrolment rates (<50%) but caught up with Kenya and overtook the rest of Africa in 2011-2015. However, Ethiopia remained well below the average African rates for undernourishment, food deficits and cell phone subscriptions. While Kenya is well-known for its high rate of mobile phone users, it is somewhat unexpected that it can be considered to be relatively food insecure compared with other African countries. However, the coexistence of strong macroeconomic growth and high rural poverty levels in Kenya suggests that causes of poverty are complex (Radeny et al., 2012).

There are interesting similarities and differences in Kenyan and Ethiopian agricultural indicators. In both countries, a comparatively large majority of people lived in rural areas. This reduced somewhat over time, while population density increased considerably as a result of rapid population growth. This is expected to continue, with Ethiopia's population of 92 million expected to grow to 160 million by 2050 (Josephson et al., 2014). Kenya is already relatively densely populated, with 40% of its rural people residing on 5% of its rural land (Muyanga & Jayne, 2014). As a result, farm sizes are relatively small. According to Table 1.1 there are clear differences in agricultural value-added. This is much lower in Ethiopia, but almost doubled over time from \$279 to \$448 per worker, while Kenya has higher value-added that remained stagnant and still relatively low at \$783 per worker in 2011-2015. Compared to other African countries both had relatively high cereal yields and fertiliser use, though much lower than global averages. It is noteworthy that Ethiopia overtook Kenya by almost doubling its cereal yield from 1,240 to 2,132 kg/ha while Kenyan yields remained stagnant at around 1600 kg/ha, despite more intensive fertiliser use. It thus seems that the two countries are on different trajectories with regard to rural development. The next two paragraphs briefly review the literature on technology adoption and transfer in the two countries.

Table 1.1 Development and agricultural indicators

	Ethiopia			Kenya			sub-Saharan Africa			World		
	2001-2005	2006-2010	2011-2015	2001-2005	2006-2010	2011-2015	2001-2005	2006-2010	2011-2015	2001-2005	2006-2010	2011-2015
Development indicators												
Poverty (% below $1.90 a day 2011 PPP)	36.3	33.5	-	33.6	-	-	-	-	-	23.9	17.5	13.4
Life expectancy at birth (years)	54.3	59.4	63.1	52.0	56.7	60.6	51.6	54.9	57.8	68.5	69.9	71.1
Primary net enrolment rate (%)	49.2	72.1	80.8	70.5	81.6	84.9	65.9	74.5	77.0	85.6	88.6	89.1
Undernourishment (% of population)	50.1	40.9	34.0	33.1	26.1	22.3	25.9	21.7	19.1	14.9	13.1	11.2
Food deficit (kcal per person per day)	402	315	258	225	180	146	191	160	137	131	118	95
Mobile cellular subscriptions (%)	0.2	3.5	24.3	6.1	40.3	70.9	6.1	31.0	62.5	23.5	59.3	90.7
Agricultural indicators												
Rural population (%)	84.7	83.4	81.4	79.0	77.2	75.2	68.0	65.7	63.3	52.0	49.5	47.1
Population density (per sq. km)	72.5	83.1	94.6	59.0	67.3	76.8	30.6	35.1	40.2	49.0	52.1	55.3
Arable land (ha per person)	0.15	0.17	0.17	0.15	0.14	0.14	0.26	0.24	0.23	0.22	0.21	0.20
Agriculture value added per worker ($)[1]	279	365	448	738	740	783	898	1,062	1,184	1,649	1,873	2,108
Cereal yield (kg / ha)	1,240	1,593	2,132	1,635	1,558	1,637	1,143	1,292	1,427	3,191	3,472	3,776
Fertiliser use (kg / ha arable land)	11.0	16.8	21.3	30.6	33.0	46.1	11.7	13.1	16.3	103.2	110.7	119.9

Source: World Development Indicators (databank.worldbank.org/wdi accessed on 4 August 2016)

[1] Measures the output of the agricultural sector less the value of intermediate inputs. Data are in constant 2010 U.S. dollars.

Ethiopia's government invested considerably in public support for agriculture, but there is limited private sector involvement and land is state-owned. Ethiopia is among the poorest countries in the world and its agricultural sector accounts for 85 percent of employment (Dercon et al., 2012; Spielman et al., 2010). Accordingly, the Ethiopian government placed agriculture at the centre of its growth strategy (Krishnan & Patnam, 2013), with improving the productivity of smallholders a policy priority (Abebaw & Haile, 2013). In addition, the government of Ethiopia increased its support for extension (Dercon et al., 2009): the number of extension agents increased from 15,000 to 65,000 between 2002 and 2009 (Gebremedhin, 2006; Spielman et al., 2010) and around 18,000 new farmer training centres were established (Gebremedhin et al., 2009). This resulted in an intensive extension system with 600 farmers assigned to one extension agent (Krishnan & Patnam, 2013). This may have prevented common weaknesses related to public extension systems (Anderson & Feder, 2007), which have been characterized in East Africa as being too disintegrated and ineffective for any technological transformation to take place (Salami et al., 2010).

Another noteworthy characteristic is that land in Ethiopia is state-owned with individuals given usufruct rights. Despite recent land certification efforts land cannot be sold, permanently exchanged for other property or mortgaged and inheritance is possible only by the immediate family (Ali et al., 2011). Moreover, it has been suggested that the state's heavy presence in the agricultural sector has now outlived its usefulness and that more consideration should be given to building a dynamic private sector, particularly with regard to input provision (Spielman et al., 2010).

Despite problematic public extension many Kenyan farmers can access agricultural technologies through the private sector. Kenya's economy is built on its agricultural sector; with over 70% of its 40 million people deriving their livelihoods from farming and farming-related activities (Zaal et al., 2012). However, the public extension system in Kenya has insufficient capacity and resources to provide small-scale farmers with adequate agricultural advice (ibid).

Nonetheless, Kenya stands as a notable departure from the common sub-Saharan African narrative concerning access to markets and improved technologies. Between 1997 and 2010, for instance, average distances farmers had to travel to access input and output markets improved considerably throughout the country (Chamberlin & Jayne, 2013). In addition, chemical fertilizer use almost doubled from 1992 to 2007, with much of the increase attributable to smallholder farmers (Ariga & Jayne, 2011). The authors related this to developments in the early 1990s, which included liberalization of fertiliser markets, elimination of government price controls and import licensing quotas and the phasing out of fertiliser donations by external donor agencies. Still, others have indicated that there remains considerable potential to increase fertiliser use in Kenya (Alene et al., 2008), with activities focused on increasing farmers' access to inputs through small-scale, independent stockists referred to as 'agro-dealers' (Odame & Muange, 2011).

1.5 Objectives and research questions

This PhD research aims to contribute to insights on the potential of technology transfer interventions to contribute to poverty reduction for smallholder farmers in sub-Saharan Africa. By better understanding how farmers decide whether and to what extent to adopt a technology, agricultural development projects can be refined to increase their effectiveness. Accordingly, the following research objectives were formulated:

1) Explore the relationship between agricultural intensification and livelihood diversification.
2) Focus on household aspirations to understand the potential for technology adoption to improve agricultural performance.
3) Determine conditions that supported the adoption of improved chickpea in Ethiopia.
4) Assess the impact of improved chickpea adoption on income and poverty reduction.
5) Investigate to what extent heterogeneity in net returns predicts adoption.

Following the problem definition and research objectives the PhD research intends to answer the following research question and sub-questions**:** *To what extent can agricultural technology transfer contribute to poverty reduction in Ethiopia and Kenya?*

1) What is the relevance of agricultural intensification for poverty reduction in rainfed farming systems where households follow diverse livelihood strategies?
    a) How important is agriculture as a livelihood strategy?
    b) Is intensification compatible with livelihood diversification?
    c) Is intensification a potential pathway from poverty?

2) What is the relationship between rural livelihood aspirations and the adoption of agricultural innovations?
    a) To what extent are rural households ‘really’ farmers – and do many of the households that we tend to call farmers actually consider themselves to be farmers?
    b) What are household livelihood aspirations and are there differences based on income portfolio, self-perception or opportunities such as agro-ecological potential or proximity to markets?
    c) How can we better understand the complex rural livelihood decision environment in order to improve targeting of interventions towards the most appropriate households and support their needs more effectively?

3) What factors drove the rapid adoption of improved chickpea in Ethiopia?
    a) What is the extent of adoption of improved chickpea varieties in the study area?
    b) What were the main determinants of improved chickpea adoption?
    c) Are economic returns to improved chickpea good predictors of adoption?

4) What has been the impact of adopting improved chickpea varieties on household welfare in rural Ethiopia?
    a) What has been the impact of improved chickpea adoption on household income?
    b) To what extent did adoption contribute to poverty reduction?
    c) Did adoption affect households differently depending on initial wealth status?

5) To what extent do net returns to improved chickpea varieties explain variation in adoption?
    a) What is the heterogeneity in returns to the adoption of improved chickpea?
    b) To what extent does heterogeneity in net returns explain differences in adoption?

1.6 Methodology

To answer the main research question and sub-questions I adopted a mixed methods approach. Hereby different methods are applied to study the same mechanics, processes and outcome patterns from different perspectives, thus anticipating alternative explanations and improving the validity of the findings through triangulation (Ton, 2012). Furthermore, I aimed to find out why rather than whether technology transfer interventions work. This was done by explicitly reconstructing relations between various technology transfer interventions and socio-economic indicators at the household level (van Rijn et al., 2012b). Measuring impact has numerous challenges including obtaining the effect of the technology for farmers that actually adopt, establishing causality by isolating differences in observed outcomes that are due to the adoption and accounting for spillovers, including those in estimates of a technology's impact (de Janvry et al., 2011). A quasi-experimental design was adopted where beneficiaries are not randomly selected and the identification of the control group is not straightforward (Wanjala & Muradian, 2013).

Research question one was answered through a comparative study of Embu and Kitui districts in eastern Kenya. Using survey data from 680 households, livelihood diversification was measured by developing a typology of livelihood clusters based on the contribution of different sources to household income and by a Herfindahl Index. Intensification was measured by an aggregate adoption index and indicators reflecting the adoption of individual agricultural technologies. The importance of agriculture as a livelihood strategy was assessed by analysing differences between districts and livelihood clusters in terms of on and off-farm income shares. Whether agricultural intensification and livelihood diversification are compatible was assessed using ordinary least squares (OLS) and poisson regression. Finally, whether households earned returns above the poverty line was explored using total income, farm income and crop income (per capita per day).

To answer research question two, we supplemented the survey conducted in 2013 with a follow-up survey in 2015, re-interviewing 624 households. The follow-up survey focused on gaining a better understanding of household livelihood aspirations and strategies using closed- and open-ended questions. We analysed demographics based on income-based livelihood clusters and a household's self-ascribed livelihood status. We also coded three open-ended questions on household livelihood aspirations and compared answers for income-based clusters and self-ascribed status. In addition, we disaggregated the analysis between the two districts to compare findings for a district with good agro-ecological potential and market access (Embu) and a district with lower agro-ecological potential and market access (Kitui). Finally, we applied the framework by Dorward et al. (2009) to assess how household aspirations can inform technology transfer interventions in the two contexts.

Answering research question three to four was done by performing an in-depth case study of improved chickpea adoption in Ethiopia. We utilized three rounds of panel data collected under the Tropical Legumes II (TLII) project. During the three survey rounds 700, 661 and 631 households were surveyed about activities in the 2006/07, 2009/10 and 2013/14 season respectively. The data analysis focused on factors influencing adoption as well as the effect of adoption on household welfare. To investigate results emerging from the panel data, I conducted focus group discussions (FGDs) with farmers and semi-structured interviews with experts in October 2015. Six villages were purposefully selected to reflect differences in market access, low and high adoption rates, as well as wealth variations. A total of seventy-one farmers participated in the FGDs.

Research question three analyses the conditions that led to the remarkable and rapid spread of improved chickpea varieties in Ethiopia: from 30 to 80% of farmers in just seven years. Panel data was applied to investigate what conditions are required for successful technology transfer interventions. First, we assessed various indicators of adoption of the various improved chickpea varieties and types. Second, we analysed the determinants of technology adoption by comparing descriptive statistics related to the technology, household characteristics and the context of adopters and non-adopters. Finally, we performed an in-depth analysis of yield and returns to improved chickpea adoption to assess its value as a determinant for adoption. We utilized fixed effects estimation and further control for time-invariant unobservables by including village time interactions.

To answer research question four, the impact of improved chickpea adoption on welfare in Ethiopia was analysed using three rounds of panel data. First, the determinants of improved chickpea adoption were estimated using a double hurdle model. A control function approach with correlated random effects was applied to control for possible endogeneity resulting from access to improved seed and technology transfer activities. Second, we estimate the impact of area under improved chickpea cultivation on household income and poverty. We apply a fixed effects instrumental variables approach where we use the predicted area under cultivation from the double hurdle model as an instrument for observed area under cultivation. Finally, results are disaggregated by landholding to explore whether the impact of adoption has heterogeneous effects.

Research question five aims to assess the extent to which heterogeneity in improved chickpea returns can explain the decision to adopt. We use a model in which the returns to adoption are allowed to vary across individuals. The theoretical model implies an underlying production function with correlated random coefficients (CRC). To estimate this model, we use the three rounds of panel data and implement an expanded version of Suri's (2011) CRC model. This CRC approach allows for households to have both an absolute advantage in farming (equivalent to a fixed effect) and a comparative advantage in adoption (a household effect that is correlated with the adoption decision). The estimation results imply that there is little heterogeneity in returns to improved chickpea.

In the final chapter of the thesis I discuss the main findings derived from the individual studies, their implications and limitations, and provide suggestions for future research.

Chapter 2
Intensify or diversify?
Agriculture as a pathway from poverty in eastern Kenya

2

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Abstract

Rainfed agriculture's potential as a pathway from poverty was explored through a comparative study of Embu and Kitui districts in eastern Kenya. Using survey data from 680 households, livelihood diversification was measured by developing a typology based on the contribution of different sources to household income and by a Herfindahl Index. Intensification was measured by an aggregate adoption index and indicators reflecting the adoption of individual agricultural technologies. More diversified households had higher incomes. Households specializing in farming in Embu earned enough income from agriculture to stay above the poverty line, but not in Kitui. Agricultural intensification appears a potential pathway from poverty in high-potential rainfed agriculture in Embu, while income diversification seems a more realistic strategy in low-potential areas like Kitui. This highlights the importance of agro-ecology and household livelihood strategies in determining the potential uptake of new technology and the benefits from intensification.

2.1 Introduction

Agriculture is deemed an important pathway for the rural poor to move out of poverty (World Bank, 2007). At the same time, there appears to be a vicious cycle in which low surplus production constrains the development of markets, reinforcing subsistence agriculture and keeping smallholders poor (Jayne & Muyanga, 2012). A potential exit from this impasse is 'intensification', which has become the new war-cry for agricultural research for development in sub-Saharan Africa (SSA). 'Sustainable intensification' is defined as the application of technology that can increase food production from existing farm land, places less pressure on the environment and does not undermine the capacity to continue producing food in the future (Garnett et al., 2013). Widespread adoption of such new technology is viewed as a promising strategy to increase productivity and reduce poverty among African smallholders.

One objection to this strategy is that the process of adoption is not straightforward and may not give the expected results. Determinants of adoption have been studied for decades (Feder et al., 1985; Foster & Rosenzweig, 2010; Sunding & Zilberman, 2001). Even where new technology increases average returns, households may not adopt (Suri, 2011). Moreover, adoption is determined largely by short-term profitability and sustainability is not necessarily an immediate concern for smallholders (Lee, 2005). African agricultural systems are heterogeneous in institutional contexts, socio-economic and agro-ecological conditions, generating multiple routes to intensification (Vanlauwe et al., 2014). This indicates the need for increased attention to barriers and disincentives to the adoption of technologies in SSA (Jack, 2011; Jayne et al., 2010). Furthermore, the evidence that intensification leads to poverty reduction is thin and mixed (Collier & Dercon, 2014; Cunguara & Darnhofer, 2011; Kassie et al., 2011). In particular, doubts have been raised about the potential of rainfed agriculture as a pathway from poverty. Over 80% of farms in SSA are now under two hectare (ha) (Lowder et al., 2014; Nagayets, 2005). On farms below one ha with a single cropping season, the additional income from new technology may be too low for crop production alone to lift smallholders above the poverty line (Harris & Orr, 2014).

A second objection is that, for many rural households, intensification may not be an appropriate strategy. Gone are the days when rural populations were assumed to be simply farmers (Freeman & Ellis, 2005; Sumberg et al., 2004). Instead, diversification is the norm (Barrett et al., 2001). Diversification can be defined as a process by which households construct a diverse portfolio of income generating activities to improve their living standards (Ellis, 1998). Diversification strategies vary widely (Barrett et al., 2005). Poorer households may diversify into low-return non-farm activities to spread risk, while others diversify into high-return non-farm activities as an alternative pathway from poverty (Haggblade et al., 2010; Stifel, 2010). Clearly, the diversification strategy followed by rural households will affect their decision to adopt new technology (Tittonell, 2007). Households with limited resources or the aspiration to step out of agriculture may not adopt new technology even when this is profitable (Tittonell et al., 2010). Moreover, as the share of farming in household income declines, the expected benefits to adoption need to increase in order for a technology to remain attractive (Sumberg et al., 2004). Alternatively, income from diversification into non-farm activities can be re-invested in agriculture to increase income from farming (Freeman & Ellis, 2005; Harris & Orr, 2014; Reardon, 1997). It is thus unclear whether intensification and diversification are competing or complementary livelihood strategies (Sumberg et al., 2004).

The general objective of this study is to assess the relevance of agricultural intensification for poverty reduction in rainfed farming systems where households follow diverse livelihood strategies. Specifically, we try to answer three questions:

1) How important is agriculture as a livelihood strategy?
2) Is intensification compatible with livelihood diversification?
3) Is intensification a potential pathway from poverty?

'Rainfed agriculture' covers many environments that differ widely in their potential for crop production. Generalisations based on a single environment are misleading. We have therefore used a comparative approach, allowing us to compare intensification as a potential pathway from poverty for high-potential and low-potential environments in eastern Kenya.

2.2 Material and methods

2.2.1 Study site selection and sampling

For comparison we selected two districts from eastern Kenya: Embu and Kitui. Rainfall across both districts is bimodal and allows two cropping seasons per year (Jaetzold et al., 2006; Tittonell et al., 2010). Maize is the most widely cultivated crop in both study areas (Odame & Muange, 2011). Embu district is sub-humid, with fertile soils, relatively high population density and good market access (Tittonell et al., 2010). Rainfall varies from 900-1,800 mm according to altitude (Jaetzold et al., 2006). At higher altitudes, farmers grow coffee, tea and macadamia, while at lower altitudes *miraa* (khat) is the main cash crop. Livestock consists primarily of high-grade dairy cattle. By contrast, Kitui district is semi-arid, with lower and more variable rainfall, particularly in the long rains (Rao et al., 2011). Our study was conducted in central Kitui, which lies on an undulating plateau at about 1,100 meters altitude and receives more rainfall (between 750-1,150 mm) than the rest of the district (Jaetzold et al., 2006). Livestock consists largely of zebu cattle for ploughing and goats.

The survey formed a baseline for an evaluation of Farm Input Promotions (FIPS) Africa's extension programme in Eastern Kenya (see Zaal et al., 2012). Forty-one villages were purposefully selected in coordination with government extension staff to ensure that intervention and control villages were similar in socio-economic and agro-ecological characteristics. 680 households were randomly selected from household lists compiled by village elders. The aim was to interview 15-20 percent of all village households. Because of the purposeful village sampling strategy our findings are not necessarily representative at district level. However, they give insights into which livelihood strategies generate returns above the poverty line in two contrasting rainfed environments.

Data was collected through a structured questionnaire. This was not a farm survey, based on continuous observation throughout the year and precise measurements of inputs and outputs. Rather, this was a household survey designed to capture the chief sources of household income, the profitability of the main farm enterprises, and whether or not farm households used a range of new technologies. For intensification, data was collected on the full range of on-farm enterprises, which captured the entire crop-livestock system. For diversification, data was collected on off-farm income such as trade, remittances and other forms of paid employment. Because of time and financial constraints, information on household income was collected using a one-off visit. To reduce recall bias and measurement errors implicit in a one-off survey, the survey questionnaire was designed to capture as full a record of household income as possible. In addition, where possible we interviewed both the head of household and their spouse. To aid recall, interviews were timed at the end of the main rainy season (September-October 2013), when information was collected on farm production in both the main rainy season and the previous season (May-June, 2013). Visits were made to farm fields but only where these were nearby. On average, each interview took two hours, which we judged the maximum length for unpaid interviews. In addition, village surveys were administered to collect data on the prices of crops, livestock and inputs, the availability of services, and the presence of agricultural and other interventions. The first author was present throughout the process of data collection.

2.2.2 Measurement: Poverty

Our objective is to assess the relevance of agricultural intensification for poverty reduction. We use the international poverty line of US dollar (USD) 1.25 per day per capita, which is expressed in Purchasing Power Parity (PPP) terms and constant 2005 prices. We realize that the 'dollar a day line' is not without criticism, but it has become the standard for measuring extreme poverty in the world (Ravallion et al., 2009). See also Deaton (2010) for a thorough discussion of the measurement of poverty and the role of PPP price indexes.

Following Harris and Orr (2014) we analyse whether total, farm or crop related activities can generate incomes above the international poverty line. Specifically, we converted net household income from Kenya shillings (KES) to USD PPP values, using 2013 conversion rates for household final consumption expenditure extrapolated from the 2011 International Comparison Program (ICP) benchmark year (World Bank, 2015b). To inflate the international poverty line to 2013 prices, we computed its equivalent in 2005 KES using 2005 PPP conversion rates. The KES poverty line in 2005 prices was subsequently inflated to 2013 prices using the Kenyan national consumer price index. Conversion of the 2013 KES poverty line into 2013 USD PPP prices translated into an international poverty line of USD 1.49 per day per capita in 2013.

2.2.3 Measurement: Livelihood diversification

Diversification was measured as the vector of income shares associated with different income sources (Barrett et al., 2005). Income sources represent net income as they take into account input and hired labour costs for crop production and livestock rearing, while households were specifically asked to report net off-farm income. Unlike Harris and Orr (2014), we did not measure net returns to specific agricultural technologies, but net returns from agriculture (excluding the cost of family labour) at household level.

We estimated two indicators of livelihood diversification. First, cluster analysis was used to assign households to clusters based on the share of on-farm, farm labour and non-farm income sources. K-means cluster analysis was performed to obtain a predetermined number of clusters to minimize within-cluster variance and maximize between cluster variance following Brown et al. (2006). Since households that engage in farm labour are likely to be poorer, it is important to study this group separately (Barrett et al., 2005; Davis et al., 2010). We therefore increased the number of clusters until it was possible to distinguish a 'farm-worker' cluster. This resulted in four clusters: full-time farmer, farm-worker, mixed and non-farm.

Second, we used the Herfindahl Index, defined as the sum of squared shares of on- and off-farm income sources (Barrett et al., 2005). Following Davis et al. (2010) we distinguished three sources of on-farm income (crop sales, value of own crop consumption and livestock income) and four sources of off-farm income (non-farm wage labour, farm labour, self-employment / trade and transfers, such as remittances and pensions). A Herfindahl Index value of 1 indicates complete dependence on one source and 0.14 indicates perfectly equal earning across the 7 income sources.

2.2.4 Measurement: Agricultural intensification

To measure intensification, we constructed an index of technology adoption. Following van Rijn et al. (2012a) and Pamuk et al. (2014) the index is based on the number of technologies adopted. The index captures a range of 15 technologies, which can be grouped in five sub-categories and includes methods to improve the management of soil fertility, water resources, crops, post-harvest handling and livestock. The index ranges from 0 to 15 and sums the adoption of agricultural technologies that are applicable across both sub-humid and semi-arid agro-ecological systems and were captured by our survey. The adoption index is derived from observational data and covers the entire crop-livestock farm system, which signifies its relevance as an indicator for agricultural intensification.

We acknowledge that this is a crude index of adoption. First, count data treats widely differing technologies as equivalent. Some authors address this problem by disaggregating the adoption index into sub-categories. For instance, van Rijn et al. (2012a), distinguished between a total and an essential innovation index, while Pamuk et al. (2014) divided their analysis into innovation sub-categories. In our case, however, 15 technologies over 5 sub-categories left insufficient variation for a meaningful sub-category analysis. Second, the adoption index does not reflect the extent or intensity of adoption. Again, data limitations prevented us developing such an index. Although we have information on the area allocated to certified maize seed and fertiliser use, this information is not available for natural resource management and post-harvest innovations. Thus, we were unable to compute a weighted adoption index that incorporates the extent of farm system intensification.

On the other hand, any index of adoption that attempts to capture intensification across the entire farm system will run into problems of assumed equivalence. Examples of measuring intensification at the farm level were hard to find. We did encounter a paper where maize system intensification was estimated using factor analysis (Muraoka et al., 2015) while Aguilar-Gallegos et al. (2015) and Dhakal et al. (2015) used the percentage of innovations adopted from within each sub-category as a measure for oil palm and agroforestry innovations respectively. However, these measures focus on specific crops or individual farm system components and do not capture intensification at the level of the farm system. Thus, the general difficulties associated with the estimation of farm system intensification combined with the limitations in our data prevented us developing a more robust index of farm system intensification.

Our approach, therefore, was to retain our admittedly imperfect index of farm level intensification but to check the robustness of this index by comparing the results with those obtained from alternative indicators of intensification that reflect the intensity or extent of adoption. We borrow from a rather extensive body of literature that analyses the relationship between intensification and certain variables of interest, e.g., institutional services (Gebremedhin et al., 2009), population density (Josephson et al., 2014; Muyanga & Jayne, 2014; Ricker-Gilbert et al., 2014) and land constraints(Headey et al., 2014). We specifically utilized the following indicators of intensification: chemical fertiliser use (kg/ha), certified maize seed use (% maize area), maize yield (kg/ha) as well as land and labour returns (USD PPP / ha or family labour day). These measures avoid concerns around treating technologies as equivalent while providing an indication of the extent of adoption. By comparing differences between the livelihood clusters with respect to these indicators we can further assess correlations between intensification and diversification. In addition, the composite indicators for returns to land and labour indicate the returns to intensification. Of course, these indicators do not reflect intensification at the level of the farm system. Since the general objective of the paper is to assess whether intensification is compatible with livelihood diversification, we have therefore chosen to retain an index of intensification at the aggregate or farm system level.

2.2.5 Analysis

We used a variety of methods to answer our three research questions. First, we assessed the importance of agriculture as a livelihood strategy (research question 1). Differences in on and off-farm income shares as well as the Herfindahl Index were analysed by district and livelihood cluster. In addition, analysis of variance (ANOVA) was performed to compare mean descriptive values across the livelihood clusters. Tests were adjusted using the Bonferroni method to correct for possible spurious inference due to making multiple comparisons between group means and proportions following Brown et al. (2006).

Secondly, we analysed whether agricultural intensification and livelihood diversification are compatible (research question 2). Ordinary least squares (OLS) regression was used to analyse the relationship between diversification and technology adoption. The main variables of interest are the livelihood clusters, with full-time farmers as comparison category, and the Herfindahl Index. The model includes various controls derived from the extensive and longstanding literature on the determinants of technology adoption (e.g., Feder et al., 1985; Foster & Rosenzweig, 2010; Jack, 2011; Lee, 2005; Parvan, 2011; Sunding & Zilberman, 2001). Descriptive statistics for the variables used in the regression models are presented in the Appendix. Because the adoption index consists of count data, Poisson models were estimated to check robustness. We further assessed the robustness of our findings by running the OLS model with alternative indicators of agricultural intensification.

Finally, we explored whether agricultural intensification is a potential pathway from poverty (research question 3). We did this by calculating whether households earned returns above the poverty line using total income per capita, farm income per capita and crop income per capita (per day and in 2013 USD PPP prices). Comparing returns to crop and farm income with total income, provides an indication of agriculture's potential contribution to poverty alleviation.

2.3 Results

How important is agriculture as a livelihood strategy? Table 2.1 shows income diversification among the sample households. In Kitui, full-time farmers accounted for just 16% of the sample population, while the majority belonged to the non-farm and mixed livelihood clusters. The share of full-time farmers in Embu was twice as high (36%), but they were still a minority. The Herfindahl Index shows that the households in the non-farm livelihood cluster were less diversified in terms of sources of income (index 0.62, 0.63) than full-time farmers (index 0.45, 0.49). The mixed livelihood cluster was the most diversified, with the lowest Herfindahl Index (0.36). Mixed farmers were less market-oriented than full-time farmers with around half the share of income from crop sales. There were significant differences between districts. The share of off-farm income was higher in Kitui (59%) while in Embu the largest share of income came from agriculture (57%). Households in Embu were also more market-oriented, drawing a higher share of income from crop sales (27%) than in Kitui (8%).

Tables 2.2 and 2.3 compare demographics, wealth and farming activities between districts and livelihood clusters. Family size and dependency rates in Kitui were higher than in Embu. Distances to roads were larger in Kitui and there was considerably less access to electricity. Average farm size in both districts was below 1 ha. Although households in Kitui owned more land, land in Embu was more valuable. The value of livestock and other assets did not differ significantly between the two districts. Chemical fertiliser rates, the number of crops planted and the share of households hiring labour were significantly higher in Embu. Returns to land in Embu (3,800 USD/ha) were more than double those in Kitui (1,712 USD/ha), while average returns to family labour were also higher (24 USD/day compared to 14 USD/day). Maize productivity was significantly higher in Embu (2,068 kg/year) than in Kitui (1,737 kg/year). A significantly higher share of households in Embu grew and sold horticultural crops (vegetables) and cash crops (coffee, tea, miraa). Households in Embu were more likely to receive information on agricultural technologies from the state extension service, whereas those in Kitui relied primarily on the mass media.

Table 2.1 Share of income by district and livelihood cluster

	Kitui	Embu	Kitui				Embu			
			Full-time farmer	Farm-worker	Mixed	Non-farm	Full-time farmer	Farm-worker	Mixed	Non-farm
	n=335	n=345	n=55	n=32	n=113	n=135	n=125	n=39	n=104	n=77
Herfindahl Index: Income diversification	$.49_a$	$.47_a$	$.45_a$	$.46_a$	$.36_b$	$.62_c$	$.49_a$	$.44_a$	$.36_b$	$.63_c$
Farm income (%)	40.7_a	56.9_b	84.9_a	33.3_b	51.7_c	15.3_d	90.0_a	38.2_b	54.1_c	16.3_d
Crop sales (%)	8.4_a	26.7_b	22.9_a	$4.9_{b,c}$	9.5_b	2.3_c	44.6_a	17.0_b	23.3_b	7.2_c
Value own consumption (%)	22.9_a	16.1_b	40.9_a	21.1_b	30.4_c	9.7_d	21.9_a	15.2_b	16.4_b	6.5_c
Livestock income (%)	9.5_a	14.1_b	21.1_a	$7.3_{b,c}$	11.8_b	3.3_c	23.5_a	$5.9_{b,c}$	14.4_b	2.6_c
Off-farm income (%)	59.3_a	43.1_b	15.1_a	66.7_b	48.3_c	84.7_d	10.0_a	61.8_b	45.9_c	83.7_d
Farm wage labour (%)	8.4_a	8.9_a	5.3_a	58.1_b	3.8_a	1.9_a	4.8_a	55.6_b	$2.0_{a,c}$	1.3_c
Non-farm wage labour (%)	29.5_a	21.3_b	5.2_a	3.6_a	22.0_b	51.8_c	2.1_a	2.9_a	23.4_b	58.9_c
Self-employment / trade (%)	11.0_a	7.2_b	1.8_a	1.6_a	9.5_a	18.3_b	1.0_a	1.9_a	11.5_b	14.3_b
Transfers (%)	10.4_a	5.7_b	2.8_a	$3.4_{a,b}$	13.1_b	$12.8_{b,c}$	2.2_a	1.3_a	9.0_b	9.2_b

Note: Values in the same row and sub-table not sharing the same subscript are significantly different at $p< .05$ in the two-sided test of equality for column means / proportions. Tests are adjusted for all pairwise comparisons within a row of each innermost sub-table using the Bonferroni correction.

Table 2.2 Analysis of variance demographics and wealth by district and cluster

	Kitui	Embu	Kitui				Embu			
			Full-time farmer	Farm-worker	Mixed	Non-farm	Full-time farmer	Farm-worker	Mixed	Non-farm
	n=335	n=345	n=55	n=32	n=113	n=135	n=125	n=39	n=104	n=77
Demographics and location										
Male head (yes=1)	$.80_{a}$	$.84_{a}$	$.82_{a}$	$.81_{a}$	$.79_{a}$	$.81_{a}$	$.85_{a}$	$.74_{a}$	$.83_{a}$	$.91_{a}$
Age household head (years)	48.98_{a}	51.31_{b}	52.58_{a}	49.44_{a}	48.95_{a}	47.43_{a}	54.56_{a}	$49.97_{a,b}$	$51.42_{a,b}$	46.57_{b}
Education head (years)	7.94_{a}	7.36_{a}	6.76_{a}	$6.72_{a,b}$	$7.96_{a,b}$	8.69_{b}	6.85_{a}	6.08_{a}	$7.48_{a,b}$	8.68_{b}
Married head (yes=1)	$.76_{a}$	$.79_{a}$	$.80_{a}$	$.75_{a}$	$.75_{a}$	$.76_{a}$	$.78_{a}$	$.69_{a}$	$.76_{a}$	$.90_{a}$
Family size (No.)	5.27_{a}	4.27_{b}	5.44_{a}	4.97_{a}	5.44_{a}	5.12_{a}	4.44_{a}	4.51_{a}	3.79_{a}	4.52_{a}
Dependents (%)	40.11_{a}	35.74_{b}	39.31_{a}	36.03_{a}	39.87_{a}	41.61_{a}	34.64_{a}	34.64_{a}	38.40_{a}	34.49_{a}
Distance to nearest all-weather road (km)	$.71_{a}$	$.53_{b}$	$.76_{a}$	$.96_{a}$	$.64_{a}$	$.69_{a}$	$.60_{a}$	$.87_{a}$	$.47_{a}$	$.33_{a}$
Access to electricity (%)	21.5_{a}	38.3_{b}	18.2_{a}	0.0_{a}	19.5_{a}	29.6_{a}	32.8_{a}	10.3_{b}	$44.2_{a,c}$	53.2_{c}
Wealth, credit and savings										
Current asset value (USD PPP)	$1,988_{a}$	$1,668_{a}$	$1,485_{a}$	806_{a}	$1,665_{a}$	$2,744_{a}$	$1,463_{a}$	546_{a}	$1,731_{a,b}$	$2,483_{b}$
Current owned land value (USD PPP)	$16,394_{a}$	$33,447_{b}$	$19,117_{a}$	$13,060_{a}$	$18,233_{a}$	$14,535_{a}$	$39,097_{a}$	$21,530_{a}$	$31,670_{a}$	$32,710_{a}$
Land owned (ha)	1.16_{a}	$.70_{b}$	1.38_{a}	$.78_{a}$	1.29_{a}	1.06_{a}	$.83_{a}$	$.42_{b}$	$.65_{a,b}$	$.70_{a,b}$
Current animal value (USD PPP)	$1,075_{a}$	936_{a}	$1,287_{a}$	552_{a}	$1,239_{a}$	975_{a}	$1,130_{a}$	439_{b}	$991_{a,c}$	$797_{b,c}$
Total current tropical livestock units (TLU)	2.06_{a}	1.39_{b}	2.57_{a}	1.06_{a}	2.36_{a}	1.85_{a}	1.67_{a}	$.65_{b}$	1.45_{a}	$1.21_{a,b}$
Has credit (%)	25.4_{a}	20.6_{a}	20.0_{a}	12.5_{a}	23.9_{a}	31.9_{a}	17.6_{a}	15.4_{a}	20.2_{a}	28.6_{a}
Has savings (%)	70.7_{a}	67.2_{a}	67.3_{a}	59.4_{a}	75.2_{a}	71.1_{a}	66.4_{a}	53.8_{a}	73.1_{a}	67.5_{a}

Note: Values in the same row and sub-table not sharing the same subscript are significantly different at $p< .05$ in the two-sided test of equality for column means / proportions. Tests are adjusted for all pairwise comparisons within a row of each innermost sub-table using the Bonferroni correction.

Table 2.3 Analysis of variance farming activities by district and cluster

	Kitui	Embu	Kitui				Embu			
			Full-time farmer	Farm-worker	Mixed	Non-farm	Full-time farmer	Farm-worker	Mixed	Non-farm
	n=335	n=345	n=55	n=32	n=113	n=135	n=125	n=39	n=104	n=77
Land, input and labour utilization										
Area cultivated (ha)	$.89_{a}$	$.64_{b}$	1.02_{a}	$.66_{a}$	1.02_{a}	$.78_{a}$	$.77_{a}$	$.43_{b}$	$.60_{a,b}$	$.58_{b}$
Organic fertiliser (kg/ha)	$1{,}054_{a}$	$1{,}155_{a}$	$1{,}113_{a}$	695_{a}	$1{,}030_{a}$	$1{,}136_{a}$	$1{,}272_{a}$	785_{a}	$1{,}423_{a}$	792_{a}
Chemical fertiliser (kg/ha)	21_{a}	193_{b}	58_{a}	17_{a}	7_{a}	18_{a}	212_{a}	115_{a}	181_{a}	216_{a}
Certified maize seed (% maize area)	67.6_{a}	86.9_{b}	66.6_{a}	64.7_{a}	63.1_{a}	72.3_{a}	$85.9_{a,b}$	71.5_{a}	90.2_{b}	$92.0_{b,c}$
Crops planted (No.)	6.8_{a}	8.7_{b}	7.8_{a}	$7.1_{a,b}$	7.0_{a}	6.1_{b}	9.2_{a}	8.1_{a}	8.7_{a}	8.3_{a}
Farm family labour days (days)	191.7_{a}	163.6_{b}	250.6_{a}	124.1_{b}	218.0_{a}	161.8_{b}	193.7_{a}	125.1_{b}	$159.3_{a,b}$	139.9_{b}
Farm hired labour days (days)	46.7_{a}	40.2_{a}	31.6_{a}	6.5_{a}	37.5_{a}	70.2_{a}	56.3_{a}	17.1_{b}	$33.5_{a,b}$	$34.9_{a,b}$
Hires labour (%)	52.2_{a}	71.0_{b}	$56.4_{a,b}$	34.4_{a}	44.2_{a}	61.5_{b}	70.4_{a}	59.0_{a}	79.8_{a}	66.2_{a}
Productivity, returns and farm system										
Land returns (crop income (USD) / ha cultivated)	$1{,}712_{a}$	$3{,}800_{b}$	$2{,}793_{a}$	878_{b}	$1{,}773_{a,b}$	$1{,}417_{b}$	$4{,}602_{a}$	$2{,}688_{a,b}$	$3{,}961_{a,b}$	$2{,}844_{b}$
Labour returns (farm income (USD) / fam. labour days)	13.8_{a}	23.9_{b}	28.2_{a}	$5.7_{a,b}$	$16.7_{a,b}$	7.4_{b}	32.6_{a}	$9.6_{a,b}$	$27.7_{a,b}$	12.0_{b}
Annual maize productivity (kg/ha)	$1{,}737_{a}$	$2{,}068_{b}$	$1{,}890_{a}$	$1{,}191_{a}$	$1{,}801_{a}$	$1{,}751_{a}$	$2{,}245_{a}$	$1{,}419_{a}$	$2{,}242_{a}$	$1{,}874_{a}$
Grows agroforestry crops (%)	77.3_{a}	97.7_{b}	81.8_{a}	75.0_{a}	83.2_{a}	71.1_{a}	99.2_{a}	97.4_{a}	99.0_{a}	93.5_{a}
Sells agroforestry crops (%)	26.9_{a}	90.7_{b}	40.0_{a}	$25.0_{a,b}$	$31.0_{a,b}$	18.5_{b}	97.6_{a}	76.9_{b}	$92.3_{a,b}$	84.2_{b}
Grows horticultural crops (%)	33.7_{a}	79.4_{b}	43.6_{a}	28.1_{a}	38.9_{a}	26.7_{a}	80.8_{a}	59.0_{b}	86.5_{a}	$77.9_{a,b}$
Sells horticultural crops (%)	10.1_{a}	42.7_{b}	25.5_{a}	3.1_{b}	$10.6_{a,b}$	5.2_{b}	49.6_{a}	33.3_{a}	43.3_{a}	35.5_{a}
Grows cash crops (%)	3.0_{a}	78.3_{b}	5.5_{a}	3.1_{a}	3.5_{a}	1.5_{a}	88.8_{a}	69.2_{b}	$77.9_{a,b}$	66.2_{b}
Sources of information accessed										
Source: Government extension (%)	23.6_{a}	36.5_{b}	29.1_{a}	9.4_{a}	30.1_{a}	19.3_{a}	43.2_{a}	17.9_{b}	$41.3_{a,b}$	$28.6_{a,b}$
Source: FIPS-Africa (%)	19.4_{a}	22.0_{a}	20.0_{a}	21.9_{a}	21.2_{a}	17.0_{a}	25.6_{a}	30.8_{a}	19.2_{a}	15.6_{a}
Source: Farmer group (%)	16.1_{a}	23.8_{b}	27.3_{a}	$21.9_{a,b}$	$15.0_{a,b}$	11.1_{b}	27.2_{a}	33.3_{a}	20.2_{a}	18.2_{a}
Source: Mass media (%)	65.1_{a}	47.0_{b}	65.5_{a}	78.1_{a}	61.9_{a}	64.4_{a}	49.6_{a}	59.0_{a}	40.4_{a}	45.5_{a}

Note: Values in the same row and sub-table not sharing the same subscript are significantly different at $p< .05$ in the two-sided test of equality for column means / proportions. Tests are adjusted for all pairwise comparisons within a row of each innermost sub-table using the Bonferroni correction.

In both districts the highest returns to land and labour were achieved by full-time farmers, while returns were lowest for farm-workers. Full-time farmers in Embu were more closely linked to markets, with a higher share selling agroforestry crops (98%) and cash crops (89%) than in Kitui (40% and 6%, respectively).

Adoption of new technology was significantly higher in Embu (adoption index = 8.98) than in Kitui (adoption index = 7.70) (Table 2.4). Households in Embu were more likely to adopt irrigation, certified maize seed, chemical fertiliser, non-storage chemicals and post-harvest innovations, whereas households in Kitui were more likely to adopt labour-intensive erosion control and water harvesting technologies and relied on organic fertiliser. Households in Embu were also more likely to own improved animal breeds and buy animal feed, reflecting their engagement in dairy and poultry farming. Within the clusters, full-time farmers had the highest adoption index (8.20, 9.57), although these are not significantly different from the mixed cluster. Non-farm households had a significantly lower adoption index (7.45, 8.38), similar to that of farm-workers. Adoption of new technology by full-time farmers was significantly higher than non-farm households only for post-harvest processing (drying, threshing/shelling and grading) reflecting their greater market-orientation.

Is intensification compatible with livelihood diversification? Table 2.5 shows regression results for determinants of technology adoption as measured by the adoption index. Model 1 captures the influence of diversification by using livelihood clusters as independent variables while Model 2 uses the Herfindahl Index. Model 1 shows that non-farm and farm-worker households had a significantly lower adoption index than full-time farmers (the comparison category). Mixed cluster households also had a lower adoption index, but this was significant only at the 10% level. Model 1 thus suggests that specialisation in farming is positively related to adoption as both non-farm and farm-worker clusters had consistently and significantly lower levels of adoption. However, full-time farmers adopt only up to one technology more than other clusters, indicating that the effect size is relatively small. Model 2 shows that the coefficient for the Herfindahl Index was negative, indicating that households with a greater variety of income sources were higher adopters. The Herfindahl Index shows that the non-farm cluster was the least diversified. When the Herfindahl Index was replaced by the share of non-farm income (not shown), the coefficient was negative and significant. Together, these results suggest that diversification out of agriculture reduced adoption. The Poisson model largely confirms the findings from the OLS models, though the mixed cluster is no longer significantly different and the Herfindahl Index is only significant at the 10% level. Other significant determinants of adoption included the tropical livestock units owned, the value of assets, distance from an all-weather road and access to electricity, all of which control for the potential effects of wealth and market access. The coefficients for all four sources of information were positive and statistically significant, confirming the importance of information for adoption. Horticulture, agroforestry or cash crop farming, were also positively correlated with adoption. Savings had a significant positive relation but access to credit was not statistically significant. Land ownership was not significantly related to adoption, suggesting that adoption was not biased towards bigger or wealthier farmers.

Table 2.4 Technology adoption index by district and livelihood cluster

			Kitui				Embu			
	Kitui	Embu	Full-time farmer	Farm-worker	Mixed	Non-farm	Full-time farmer	Farm-worker	Mixed	Non-farm
	n=335	n=345	n=55	n=32	n=113	n=135	n=125	n=39	n=104	n=77
Adoption index (No. technologies)	7.70_a	8.98_b	8.20_a	7.06_b	$7.94_{a,b}$	7.45_b	9.57_a	7.95_b	$9.11_{a,c}$	$8.38_{b,c}$
Irrigation (%)	6.3_a	13.6_b	10.9_a	6.3_a	3.5_a	6.7_a	15.2_a	7.7_a	18.3_a	7.8_a
Erosion control and water harvesting (%)	93.7_a	63.2_b	92.7_a	100.0_a	96.5_a	90.4_a	68.0_a	53.8_a	63.5_a	59.7_a
Conservation agriculture (%)	12.8_a	8.1_b	16.4_a	6.3_a	16.8_a	9.6_a	8.0_a	15.4_a	4.8_a	9.1_a
Intercropping (%)	96.7_a	92.8_b	98.2_a	96.9_a	98.2_a	94.8_a	91.2_a	94.9_a	93.3_a	93.5_a
Certified maize seed (%)	80.3_a	91.6_b	78.2_a	78.1_a	78.8_a	83.0_a	$90.4_{a,b}$	79.5_a	95.2_b	$94.8_{a,b}$
Selectively saves seed (%)	72.5_a	73.3_a	78.2_a	87.5_a	68.1_a	70.4_a	79.2_a	87.2_a	66.3_a	66.2_a
Organic fertiliser (%)	66.6_a	37.1_b	80.0_a	56.3_a	70.8_a	60.0_a	40.0_a	35.9_a	40.4_a	28.6_a
Chemical fertiliser (%)	16.7_a	91.9_b	12.7_a	12.5_a	12.4_a	23.0_a	95.2_a	79.5_b	$92.3_{a,b}$	$92.2_{a,b}$
Chemicals - excluding pesticides (%)	8.7_a	23.8_b	16.4_a	12.5_a	4.4_a	8.1_a	24.0_a	15.4_a	26.9_a	23.4_a
Pesticides - including storage (%)	87.2_a	79.4_b	80.0_a	78.1_a	90.3_a	89.6_a	82.4_a	69.2_a	84.6_a	72.7_a
Improved storage (%)	80.3_a	79.4_a	$74.5_{a,b}$	65.6_a	86.7_b	$80.7_{a,b}$	85.6_a	69.2_a	78.8_a	75.3_a
Post-harvest processing (%)	33.4_a	59.4_b	56.4_a	$31.3_{a,b}$	38.9_a	20.0_b	77.6_a	$64.1_{a,b}$	50.0_b	$40.3_{b,c}$
Improved animal breeds (%)	8.4_a	52.2_b	12.7_a	0.0_a	12.4_a	5.2_a	57.6_a	33.3_b	$52.9_{a,b}$	$51.9_{a,b}$
Buys animal feed (%)	26.9_a	53.0_b	27.3_a	12.5_a	31.0_a	26.7_a	57.6_a	20.5_b	61.5_a	50.6_a
Other animal services (%)	79.7_a	79.1_a	$85.5_{a,b}$	62.5_a	85.0_b	$77.0_{a,b}$	84.8_a	69.2_a	81.7_a	71.4_a

Note: Values in the same row and sub-table not sharing the same subscript are significantly different at $p < .05$ in the two-sided test of equality for column means / proportions. Tests are adjusted for all pairwise comparisons within a row of each innermost sub-table using the Bonferroni correction.

Table 2.5 OLS and Poisson Regression – Dependent variable: Adoption Index (No. technologies)

Variables	Model 1: OLS	Model 1: Poisson	Model 2: OLS	Model 2: Poisson
Male head (yes=1)	-0.32598	-0.04544	-0.35362	-0.04677
	(0.282)	(0.063)	(0.285)	(0.063)
Age household head (years)	0.00043	0.00000	0.00121	0.00012
	(0.005)	(0.001)	(0.005)	(0.001)
Education head (years)	0.00490	0.00057	0.00581	0.00077
	(0.020)	(0.004)	(0.020)	(0.004)
Married head (yes=1)	0.63921**	0.08491	0.68648***	0.08940
	(0.260)	(0.058)	(0.263)	(0.058)
Household size (No.)	0.01135	0.00134	0.00681	0.00094
	(0.033)	(0.007)	(0.033)	(0.007)
Dependents (%)	-0.00551**	-0.00065	-0.00495*	-0.00059
	(0.003)	(0.001)	(0.003)	(0.001)
Access to electricity (yes=1)	0.33783**	0.03676	0.32247**	0.03399
	(0.163)	(0.034)	(0.162)	(0.033)
Distance to nearest all-weather road (km)	0.12077**	0.01436	0.11346**	0.01332
	(0.057)	(0.012)	(0.057)	(0.012)
Current asset value (USD PPP)	0.00004*	0.00000	0.00004*	0.00000
	(0.000)	(0.000)	(0.000)	(0.000)
Land owned (ha)	-0.04920	-0.00520	-0.03871	-0.00459
	(0.072)	(0.015)	(0.073)	(0.015)
Tropical livestock units owned (No.)	0.16789***	0.01927***	0.17568***	0.02027***
	(0.034)	(0.007)	(0.034)	(0.007)
Has credit (yes=1)	-0.12221	-0.01685	-0.13520	-0.01874
	(0.159)	(0.034)	(0.159)	(0.034)
Has savings (yes=1)	0.48283***	0.05966*	0.47509***	0.05871*
	(0.147)	(0.031)	(0.147)	(0.031)
Grows horticultural crops (yes=1)	0.61302***	0.07471**	0.63142***	0.07683**
	(0.152)	(0.032)	(0.153)	(0.033)
Grows agroforestry crops (yes=1)	0.57837***	0.08308*	0.56894***	0.08046*
	(0.213)	(0.048)	(0.215)	(0.048)
Grows cash crops (yes=1)	0.43790**	0.04894	0.54112***	0.06113
	(0.209)	(0.044)	(0.209)	(0.043)
Source: Government extension (yes=1)	0.36764**	0.04313	0.44117***	0.05276*
	(0.146)	(0.030)	(0.147)	(0.030)
Source: FIPS-Africa (yes=1)	0.56231***	0.06463**	0.54499***	0.06338*
	(0.161)	(0.033)	(0.162)	(0.033)
Source: Farmer group (yes=1)	0.38673**	0.04491	0.36390**	0.04175
	(0.165)	(0.034)	(0.166)	(0.034)
Source: Mass media (yes=1)	0.64598***	0.07837***	0.61427***	0.07432***
	(0.135)	(0.029)	(0.136)	(0.028)
Cluster: Farm-worker (yes=1)	-0.93649***	-0.11413**		
	(0.240)	(0.052)		
Cluster: Mixed (yes=1)	-0.29080*	-0.03024		
	(0.173)	(0.035)		
Cluster: Non-farm (yes=1)	-0.67322***	-0.07854**		
	(0.186)	(0.039)		
Herfindahl Index: Income diversification			-1.04557***	-0.13340*
			(0.363)	(0.077)
District (1=Embu, 0=Kitui)	0.52444**	0.06553	0.53670**	0.06682
	(0.215)	(0.046)	(0.216)	(0.046)
Constant	5.85769***	1.80033***	5.84647***	1.80408***
	(0.473)	(0.101)	(0.498)	(0.106)
Observations	680	680	680	680
Adjusted R-squared	0.365		0.354	
Pseudo R-squared		0.0441		0.0427

Note: cluster comparison full-time farmer, standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

To test the robustness of our findings we ran the OLS model described in the previous paragraph with various alternative indicators of intensification (Table 2.6). We report differences between the various livelihood clusters, using the full-time farmer cluster as the category for comparison. In contrast with the insignificant differences reported in Table 2.3, controlling for alternative determinants of adoption shows that farm-workers and mixed households used significantly less fertiliser than full-time farmers. However, these differences were not large, only -68 kg/ha for farm-workers and -36 kg/ha for mixed farm households, compared to full-time farmers, and the percentage of maize land cultivated with certified seed was not significantly different for any of the clusters. However, the difference in maize yields was both statistically significant and large. Maize yields for farm-workers were 841 kg/ha lower than for full-time farmers, and maize yields for non-farm households were 461 kg/ha lower. Interestingly, yields for non-farm households were lower despite their similar use of fertiliser and certified seed as full-time farmers, and again in contrast with the insignificant differences shown in Table 2.3. Moreover, the difference in returns to land and labour between the clusters was both statistically significant and large. Farm-workers and non-farm households generated 1,700 USD/ha less than full-time farmers. Returns to land for mixed households were 900 USD/ha lower. As average returns to land were 2,771 USD/ha (Table 2.A), full-time farming was considerably more profitable than among the other clusters.

Table 2.6 OLS models utilizing various indicators of agricultural intensification

Models (Dependent variable)	(1) Cluster: Farm-worker (yes=1)	(2) Cluster: Mixed (yes=1)	(3) Cluster: Non-farm (yes=1)
(1) Adoption Index (No.)	-0.9365***	-0.2908*	-0.6732***
	(0.240)	(0.173)	(0.186)
(2) Chemical fertiliser use (kg/ha)	-68.3937**	-37.5995*	-18.1215
	(27.116)	(19.487)	(20.954)
(3) Certified maize seed (% maize area)	-5.9395	-1.2893	3.2445
	(4.909)	(3.528)	(3.794)
(4) Maize yield (kg/ha)	-840.7931***	-201.9022	-461.1982**
	(274.312)	(197.134)	(211.973)
(5) Land return (USD PPP / ha)	-1,739.8252***	-907.9936**	-1,708.2795***
	(525.425)	(377.597)	(406.020)
(6) Labour return (USD PPP / day)	-14.4824**	-10.0656**	-25.6750***
	(6.397)	(4.597)	(4.943)

Note: Columns present results for the livelihood cluster variables with the full-time farmer cluster as comparison category. Rows present regression models with various indicators of agricultural intensification as dependent variables. Row (1) reports, for purposes of comparison, the results found in Table 2.6 for the adoption index OLS model. Rows (2 - 4) report results for fertiliser and improved certified maize seed use as well as maize productivity while rows (5 - 6) show results for returns to land and labour. Regressions include all explanatory variables from Table 2.6 and contain 680 observations. Standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

Is intensification a potential pathway from poverty? Table 2.7 compares income and poverty across the four livelihood clusters. Income per capita was significantly lower in Kitui than in Embu (USD 1,045 compared to USD 1,391). Consequently, poverty was also higher in Kitui, with 44% of the sample households below the poverty line compared to 33% in Embu.

Table 2.7 Analysis of variance income and poverty by district and cluster

	Kitui	Embu	Kitui				Embu			
			Full-time farmer	Farm-worker	Mixed	Non-farm	Full-time farmer	Farm-worker	Mixed	Non-farm
	(n=335)	(n=345)	(n=55)	(n=32)	(n=113)	(n=135)	(n=125)	(n=39)	(n=104)	(n=77)
Income and poverty										
Household income (USD PPP)	$4,677_{a}$	$5,053_{a}$	$3,789_{a}$	$1,617_{a}$	$3,805_{a}$	$6,493_{b}$	$4,532_{a}$	$2,397_{a}$	$4,589_{a}$	$7,870_{b}$
Income per capita (USD PPP)	$1,045_{a}$	$1,391_{b}$	743_{a}	391_{a}	811_{a}	$1,518_{b}$	$1,184_{a,b}$	597_{a}	$1,497_{b,c}$	$1,987_{c}$
Poverty - based on total income (%)	43.9_{a}	33.3_{b}	60.0_{a}	90.6_{b}	49.6_{a}	21.5_{c}	$37.6_{a,b}$	59.0_{a}	24.0_{b}	$26.0_{b,c}$
Poverty - based on net farm income (%)	85.4_{a}	55.7_{b}	67.3_{a}	100.0[1]	81.4_{a}	92.6_{b}	37.6_{a}	89.7_{b}	46.2_{a}	80.5_{b}
Poverty - based on net crop income (%)	91.3_{a}	69.0_{b}	76.4_{a}	100.0[1]	91.2_{b}	95.6_{b}	55.2_{a}	92.3_{b}	63.5_{a}	87.0_{b}
Income quartile										
Quartile 1 (%)	24.8_{a}	24.9_{a}	$34.5_{a,b}$	62.5_{a}	26.5_{b}	10.4_{c}	$27.2_{a,b}$	46.2_{a}	21.2_{b}	$15.6_{b,c}$
Quartile 2 (%)	25.1_{a}	24.9_{a}	30.9_{a}	25.0_{a}	31.0_{a}	17.8_{a}	$26.4_{a,b}$	43.6_{a}	$23.1_{a,b}$	15.6_{b}
Quartile 3 (%)	25.1_{a}	25.2_{a}	18.2_{a}	12.5_{a}	24.8_{a}	31.1_{a}	$28.0_{a,b}$	7.7_{a}	31.7_{b}	$20.8_{a,b}$
Quartile 4 (%)	25.1_{a}	24.9_{a}	16.4_{a}	0.0[1]	17.7_{a}	40.7_{b}	$18.4_{a,b}$	2.6_{a}	24.0_{b}	48.1_{c}

Note: Values in the same row and sub-table not sharing the same subscript are significantly different at $p < .05$ in the two-sided test of equality for column means / proportions. Tests are adjusted for all pairwise comparisons within a row of each innermost sub-table using the Bonferroni correction.

[1] This category is not used in comparisons because its column proportion is equal to zero or one.

Results for the livelihood clusters show that income per capita was significantly higher for non-farm households in Kitui (USD 1,518) and Embu (USD 1,987). The majority of non-farm households (70%) belonged to the two highest income quartiles. For full-time farm households, income per head was considerably higher in Embu (USD 1,184) than in Kitui (USD 743). In terms of poverty, 60% of full-time farm households in Kitui lived below the poverty line, compared to 38% in Embu. Two thirds of full-time farmers in Kitui (66%) belonged to the two poorest income quartiles compared to approximately half in Embu (54%). The poorest households were farm-workers, with 91% in Kitui and 59% in Embu living below the poverty line.

2.4 Discussion

2.4.1 Intensification and diversification

Intensification assumes that rural households are willing to adopt new technologies. To some degree, this willingness will depend on their existing livelihood strategies. Rural livelihoods in Kitui and Embu were diverse, with full-time farming a minority occupation. The majority of rural households did not depend on agriculture for their livelihood but drew most of their income from other sources (Table 2.1). For most rural households, therefore, farming was a part-time occupation. Agriculture remained important to these households, however. All our sample households, irrespective of livelihood strategy, cultivated some land, grew a variety of crops and most received income from crop sales. One-third of household income for farm-worker households came from their own farm (Table 2.1). Similarly, non-farm households use 140-162 family labour days/year working their own farms. However, the prevalence of part-time farming raises doubts about the relevance of agricultural intensification. How compatible with livelihood diversity is a strategy for poverty reduction based on widespread adoption of new farming technology?

Not surprisingly, the most eager adopters of new technology were full-time farmers. Of the 15 technologies represented in our adoption index, they had adopted eight or nine (Table 2.4). This supports the argument that farm-based households are more likely to adopt as they are focussed on increasing the profitability of their farm systems (Tittonell et al., 2010). However, part-timers were not far behind. In Kitui, for example, farm-worker households had adopted seven and mixed households eight technologies, while in Embu farm-workers and non-farm households had both adopted eight. Hence, although the difference in adoption between full-timers and part-timers was statistically significant, it was small. In Embu, for instance, adoption rates between full-time farmers and farm-workers differed significantly for only three technologies, all of which required cash investment. The situation was similar for non-farm households, which revealed few significant differences with full-time farmers. This supports suggestions that off-farm income is re-invested in crop production (Freeman & Ellis, 2005; Harris & Orr, 2014; Iiyama et al., 2008; Reardon, 1997). Therefore, intensification seems to be compatible with diversification, even in regions like eastern Kenya where part-time farming is the norm.

Although all households had adopted new technology, they did not enjoy the same level of benefits. Full-time farmers in both districts managed to generate up to twice the returns to land and farm labour compared to the other three clusters. In addition, although all households engaged in agroforestry, horticulture and cash cropping, full-time farmers were more likely to sell them, particularly in Embu. Full-time farmers generated superior returns to land and labour and had higher maize yields despite similar fertiliser use and certified maize seed adoption (Table 2.6). While a minority of rural households made a living out of agriculture, therefore, others farmed for different reasons (Tittonell, 2007). Better-off non-farm households may feel a cultural attachment to agriculture as a way of life and may be willing to pay to maintain the family farm (Barrett et al., 2001). Others may keep one foot in agriculture to avoid becoming over-dependent on non-agricultural jobs (Banerjee & Duflo, 2007). As part-time farmers, however, the benefits they receive from new technology will be relatively small (Sumberg et al., 2004). Consequently, although technology adoption may be compatible with livelihood diversification, the benefits from adoption will vary according to the household's level of engagement in farming. As a strategy to increase rural income, intensification is most effective when it targets full-time farmers.

How can the benefits from intensification be increased? One suggestion is farm consolidation, with a large proportion of the rural population becoming farm labourers (Vanlauwe et al., 2014). Farm-workers in Kitui and Embu had the highest poverty rates, a lower adoption index, the lowest returns and maize yields and owned less land and livestock. They persist with farming to utilise their limited assets and ensure some household food security. Increasing their numbers seems a dire prospect given the high prevalence of poverty in this group. Furthermore, because of their greater dependence on agriculture for their income, farm-workers are most vulnerable to agricultural yield fluctuations and price shocks (Barrett et al., 2005). Labour in impoverished households is sold cheaply to wealthier households, reinforcing the gap between rich and poor (Tittonell, 2014). This implies a self-reinforcing circle of unequal distribution of land and non-farm earnings with substantial wealth-differentiated barriers (Barrett et al., 2001). Social protection programmes may be a more effective strategy to assist these households than intensification (Tittonell et al., 2010).

2.4.2 Intensification and poverty

Livelihood clusters showed a welfare ordering with some enjoying higher incomes than others (Stifel, 2010). Farm-worker households had the lowest incomes and were concentrated in the two poorest income quartiles. Mixed cluster households had incomes somewhere between the high-return non-farm and low-return farm-worker clusters. This is caused by their engagement in different income generating activities with varying returns. By contrast, households in the non-farm livelihood cluster had the highest incomes. Over 40% of households in this cluster were in the top income quartile and more than 75% were above the poverty line (Table 2.7). This confirms the role of diversification into non-farm activities as a primary pathway from poverty (Narayan et al., 2000). Although they diversified out of agriculture, the high value of the Herfindahl Index shows that non-farm households had the least diversified incomes. Higher incomes were thus associated with specialisation into non-farm activities rather than a diversified income portfolio spread across a variety of sources.

Earlier work suggested that agricultural intensification alone could not lift smallholders above the poverty line, unless combined with diversification into non-farm activities (Harris and Orr, 2014). We explore this by comparing the percentage of households above the poverty line based on their total, farm and crop income per day per capita (Table 2.7). In Embu, 44% of households generated enough farm income (crop and livestock) to cross the poverty line compared with 64% of households if off-farm income was included. In Kitui, only 15% of households would have crossed the poverty line with farm income alone compared with 46% once off-farm income was taken into account. When we include only income from crops, as did Harris and Orr (2014), 31% of households in Embu and 9% percent of households in Kitui earned an income above the poverty line. On average, farm and crop income alone did not generate incomes above the poverty line.

Despite their small average farm size (1.0 ha in Kitui and 0.8 ha in Embu) many full-time farmers were able to generate quite high returns from crop production and livestock. Combined with off-farm income, this was enough for a significant share of full-time farmers to earn incomes above the poverty line. In Embu, farm income alone was sufficient to keep 62% of the full-time farmers out of poverty (Table 2.7). Full-time farmers in Kitui were poorer, with only 40% above the poverty line based on total income and 33% based on farm income. Crop income alone would have kept 45% in Embu and 24% in Kitui out of poverty, indicating the importance of mixed crop-livestock systems (Thornton & Herrero, 2015). Recall that full-time farmers in both districts had the highest adoption rates for new technology. The results thus indicate that intensification has potential to reduce poverty for full-time farmer households.

2.4.3 Agro-ecology and market access

Although Kitui and Embu are both rainfed farming systems, the contrast between them is striking. Full-time farmers in Embu were noticeably more commercialised than in Kitui, with a higher share of income from crop sales (45% compared to 23%) (Table 2.1). This can be correlated with the more widespread production of horticultural and cash crops, together with higher use of chemical fertiliser (Table 2.3). Clearly, farmers in Embu benefit from higher and more reliable rainfall, which provides two full growing seasons. Combined with fertile soils, better market access and greater access to state extension services, this has enabled full-time farmers in Embu to earn almost twice the returns to land than their counterparts in Kitui. High-value cash crops, horticulture and dairy farming are characteristic of households above the poverty line (Radeny et al., 2012). Similarly, dynamic agricultural regions like Embu exemplify a virtuous cycle, with technology adoption leading to agricultural surpluses and opportunities for trade that stimulate the non-farm economy (Haggblade et al., 2010).

By contrast, the benefits from intensification in low-potential zones like Kitui appear more restricted, with rural households forced out of farming into low-return non-farm activities or farm labour. Although households in Kitui cultivated more land and had more available labour than in Embu, this was insufficient to compensate for inferior rainfall and market access. Households in semi-arid systems are more reluctant to adopt new technology because of the higher risk of crop failure (Ogada et al., 2010). In addition, smallholders in remote disadvantaged areas of Kenya are faced with higher input costs, lower output prices, fewer buyers and weak access to extension (Chamberlin & Jayne, 2013). Together with lower agricultural potential, these factors reduce the incentives for the adoption of new technology and help explain the lower adoption index in Kitui. Favourable soils and rainfall can tilt the scales sufficiently to make full-time farming a profitable occupation associated with a higher standard of living. The contrasting tale of these two regions thus suggests that it is unwise to generalise about 'rainfed agriculture'.

2.5 Conclusions

The ability of smallholder agriculture in SSA to deliver widespread poverty reduction is the subject of debate. In particular, the relative merits of agricultural intensification or livelihood diversification as pathways from poverty require critical scrutiny. On farms of just 1 ha, how realistic is the hope that intensification can generate incomes above the poverty line?

A comparative study of high-and low-potential agricultural zones in eastern Kenya showed that full-time farming was a minority occupation; the majority of households were part-time farmers who received most of their income from farm labour or non-farm activities. Although full-time farmers had adopted a greater number of new technologies, part-timers had also adopted. Intensification was therefore compatible with livelihood diversity. Consequently, 'intensify' or 'diversify' is not a binary choice, as these two livelihood strategies are best seen as complementary. Among part-timers, agriculture may primarily be a source of household food security, rather than cash income. Given the risk of relying on markets for staple food supply and the scarcity of alternative employment opportunities, agriculture remains essential for rural households, irrespective of their dominant livelihood strategy. However, the returns to intensification were much lower for part-timers, particularly farm-worker households.

Although households that had diversified into non-farm activities had higher average incomes, a high share of full-time farmers in the high-potential zone had incomes above the poverty line. This was facilitated by two growing seasons, high value cash crops and horticulture, dairy farming and good market access. Thus, intensification may be a viable pathway from poverty for rainfed agriculture in high-potential environments. For full-time farmers in a low-potential environment, however, agricultural technologies offer reduced benefits, making intensification a riskier strategy than diversification into non-farm activities. Once again, intensification will have limited benefits for the poorest farm-worker households with fewer assets.

The contrasting benefits from intensification between high- and low-potential agricultural zones suggest the need to avoid generalisations about rainfed agriculture and to evaluate intensification across a spectrum of rainfed farming systems. The semi-arid and sub-humid zones compared here are at opposite ends of this spectrum. Further research is required to determine how much the benefits from adoption vary across these systems. The heterogeneity of farming systems and variations in market access suggests that these benefits vary widely, but that under favourable conditions new technology has the potential to offer full-time farmers a pathway from poverty.

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Appendix

Table 2.A Descriptive statistics for variables used in the regression models

Variables	(1) N	(2) Mean	(3) St. Dev.
Adoption index (No.)	680	8.350	2.064
Chemical fertiliser use (kg/ha)	680	108.0	206.6
Certified maize seed (% maize area)	680	77.39	37.13
Maize yield (kg/ha)	680	1,905	1,938
Land return (USD PPP / ha)	680	2,771	3,941
Labour return (USD PPP / day)	680	18.93	47.04
Male head (yes=1)	680	0.824	0.382
Age household head (years)	680	50.16	15.16
Education head (years)	680	7.644	4.029
Married head (yes=1)	680	0.778	0.416
Household size (No.)	680	4.760	2.109
Dependents (%)	680	37.89	25.82
Access to electricity (yes=1)	680	0.300	0.459
Distance to nearest all-weather road (km)	680	0.620	1.166
Current asset value (USD PPP)	680	1,826	3,454
Land owned (ha)	680	0.927	1.088
Tropical livestock units owned (No.)	680	1.721	2.286
Has credit (yes=1)	680	0.229	0.421
Has savings (yes=1)	680	0.690	0.463
Grows horticultural crops (yes=1)	680	0.569	0.496
Grows agroforestry crops (yes=1)	680	0.876	0.329
Grows cash crops (yes=1)	680	0.412	0.493
Source: Government extension (yes=1)	680	0.301	0.459
Source: FIPS-Africa (yes=1)	680	0.207	0.406
Source: Farmer group (yes=1)	680	0.200	0.400
Source: Mass media (yes=1)	680	0.559	0.497
Cluster: Full-time farmer (yes=1)	680	0.265	0.442
Cluster: Farm-worker (yes=1)	680	0.104	0.306
Cluster: Mixed (yes=1)	680	0.319	0.466
Cluster: Non-farm (yes=1)	680	0.312	0.464
Herfindahl Index: Income diversification	680	0.481	0.185
District (1=Embu, 0=Kitui)	680	0.507	0.500

Chapter 3
Who are those people we call farmers? Rural Kenyan aspirations and realities

3

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Abstract

Rural Kenyan households have different aspirations and income portfolio strategies, including agricultural intensification and income diversification. We interviewed 624 households to explore rural aspirations and derive lessons for agricultural technology development and transfer. Though few households specialized in farming, many households self-identified as farmers and aspired to increase their agricultural income. Despite the prevalence of agricultural aspirations, few aspired a future for their children in farming. Combining aspirations with potential to invest, we provide suggestions for targeting agricultural interventions. We need to start listening better to those people we call ‘farmers’ to develop and offer innovations that meet their realities.

3.1 Introduction

Rural households in sub-Saharan Africa (SSA) are among the poorest and most food insecure people in the world. A large part of African agricultural production originates from smallholder farmers and rapid population growth calls for increased food production (Ricker-Gilbert et al., 2014). Accordingly, improving the agricultural performance of African farmers has been proposed as a potential win-win intervention to solve the dual problems of poverty and hunger (Dercon et al., 2009). Many African governments and international development agencies therefore focus on improving the welfare of smallholders. The literature identifies two pathways, often overlapping, for rural households to escape from poverty: (i) intensification through the adoption of agricultural technologies, and (ii) diversification into non-farm activities. We briefly outline the arguments for each pathway in the next paragraphs.

Agricultural intensification is based on the premise that agricultural technologies offer considerable promise to improve yields in rural Africa (Dzanku et al., 2015). Moreover, since 2008 the jump in world food prices has made farming more profitable for those with sufficient agricultural land using modern inputs (Jayne et al., 2014). However, achieving agricultural intensification in SSA has proved challenging as evidenced by continued low levels of technology adoption and persistent yield gaps (Tittonell & Giller, 2013). An important research question is therefore why agricultural innovations are under-adopted. A longstanding and extensive body of research has identified various determinants of agricultural technology adoption (e.g., Feder et al., 1985; Foster & Rosenzweig, 2010): farm size, risk preference, human capital, labour availability, credit constraints, land tenure, access to input and output markets, information asymmetries or a combination of the above. It is therefore surprising that Glover et al. (2016) conclude that there is still little coherent understanding of technological change in smallholder African agriculture. This is not to say that the agricultural research community has not contributed to smallholder welfare in Africa. Indeed, many studies cite high economic returns on investments in agricultural research on a national- or global level (e.g., Renkow & Byerlee, 2010).

Gone should be the days when rural populations were assumed to be simply farmers, as diversification is the norm (Barrett et al., 2001). Diversification can be defined as a process by which households construct a diverse portfolio of income generating activities to improve their living standards (Ellis, 1998). Many farmers work part time outside agriculture, while others aim to step completely out of agriculture by migrating to cities or specializing in non-farm activities (Dorward et al., 2009). Indeed, rural households have diverse livelihood strategies and long-term aspirations and agricultural innovations need to be compatible with this diverse activity portfolio (Sumberg, 2005). These dynamics should be taken into account when targeting technological innovations and rural development efforts.

At the same time, doubts have been raised about the potential of rainfed agriculture as a pathway from poverty. Over 80% of farms in SSA are now under two hectares (ha) (Lowder et al., 2014). Whether large or small farms are more productive is a continuing debate. It is true that small farms can produce very high yields per hectare and may be more efficient than many larger farms, but the absolute value of outputs will always tend to be small on a small farm. On small farms in the semi-arid and dry sub-humid tropics of Africa and Asia, best-practice agricultural technologies, despite resulting in large percentage increases in yield and profitability, did not provide enough income per household to lift smallholders above the poverty line (Harris & Orr, 2014). Moreover, without attention to sustained agricultural productivity growth, small farms in Africa can become increasingly unviable economic units (Jayne et al., 2010). Collier and Dercon (2014) even argued that it might be time to think more seriously about larger scale agricultural development and migration out of agriculture by poor households. The future role of smallholder agricultural producers in global food production is thus highly uncertain (Herrero et al., 2014). In the meantime, however, there is a large and increasing rural population with limited attractive alternatives to farming (Jayne et al., 2014). The question is, therefore, in what ways agricultural research for development (AR4D) efforts can be reshaped to better target the needs of rural households in Africa.

Against this background, this explorative study focuses on the often overlooked aspect of household aspirations to understand better the potential for technology adoption to improve agricultural performance. Sumberg (2005) indicated that often too little attention is paid to the fact that successful adoption is dependent on people and their aspirations. We build upon research by Verkaart et al. (2017b) who found that the agricultural performance of households diversifying away from farming was lower than that of so-called ‘full-time farmers’. Though some people may just have better farming skills, additional factors may underlie this divergence in agricultural performance. As resources are scarce and the need to reduce poverty and increase food production urgent, observed differences in livelihood strategies of smallholders and associated differences in agricultural performance lead to pertinent questions:

1) To what extent are rural households ‘really’ farmers – and do many of the households that we tend to call farmers actually consider themselves to be farmers?
2) What are household livelihood aspirations and are there differences based on income portfolio, self-perception or opportunities such as agro-ecological potential or proximity to markets?
3) How can we better understand the complex rural livelihood decision environment in order to improve targeting of interventions towards the most appropriate households and support their needs more effectively?

3.2 Materials and methods

For comparison we selected two contrasting districts from eastern Kenya: Embu and Kitui. Rainfall varies from 900-1,800 mm according to altitude and is bimodal across both districts, allowing two cropping seasons per year (Jaetzold et al., 2006). Maize is the most widely cultivated crop in both study areas. Embu district is sub-humid, with fertile soils, relatively high population density and good market access. At higher altitudes, farmers grow coffee, tea and macadamia, while at lower altitudes *miraa* (khat) is the main cash crop. Livestock consists primarily of high-grade dairy cattle and both input and output market access is good.

By contrast, Kitui district has poorer market access and is semi-arid, with lower and more variable rainfall. Our study was conducted in central Kitui, which lies on a plateau at about 1,100 meters altitude and receives between 750-1,150 mm rainfall (Jaetzold et al., 2006). Livestock consists largely of goats and zebu cattle.

Our data is collected using a structured household survey conducted in 2013 and a follow-up survey in 2015. 41 villages were purposively selected and our findings are therefore not necessarily representative at district level. 684 households were randomly selected from lists compiled by village elders. Data was collected through a structured questionnaire designed to capture the chief sources of household income, the profitability of the main farm enterprises, and whether or not farm households used a range of new technologies. Income sources represent net income as they take into account input and hired labour costs for crop production and livestock rearing, while households were specifically asked to report net off-farm income. We did not measure net returns to specific agricultural technologies, but net returns from agriculture (excluding the cost of family labour) at household level. To aid recall, interviews were timed at the end of the main rainy season (September-October 2013), when information was collected on farm production in both the main rainy season and the previous season (May-June, 2013). In 2015, we re-interviewed 624 households from 2013, giving an attrition rate of nine percent. This follow-up survey focused on gaining a better understanding of household livelihood aspirations and strategies using closed- and open-ended questions.

Most descriptives are based on the 2013 data. We therefore only explicitly indicate where information is derived from the 2015 sample. To facilitate the interpretation of our monetary data we converted amounts captured in Kenya shillings (KES) to USD in Purchasing Power Parity (PPP) values. This was done using 2013 conversion rates for household final consumption expenditure extrapolated from the 2011 International Comparison Program (ICP) benchmark year. Based on this, we use the international poverty line of US dollar (USD PPP) 1.25 per day per capita at constant 2005 prices. To inflate the international poverty line to 2013 prices, we computed its equivalent in 2005 KES using 2005 PPP conversion rates. The KES poverty line in 2005 prices was inflated to 2013 prices using the Kenyan national consumer price index. Conversion of the 2013 KES poverty line to 2013 USD PPP prices translated into an international poverty line of USD 1.49 per day per capita in 2013.

To answer the first research question we compared income-based livelihood clusters with a household's self-ascribed livelihood status. We used cluster analysis to assign households to livelihood clusters based on the share of on-farm, farm labour and non-farm income sources earned in 2013. This resulted in four clusters: full-time farmer, mixed income, farm-worker and non-farm. For details see Verkaart et al. (2017b). We then assessed a household's self-ascribed livelihood status by asking respondents: 'Out of the words below, which do you think best describes your household?' With the following categories to choose from: farm household, business household, wage earners or other. The answers were coded to distinguish between farmer- and non-farmer households. We use the answers to compare self-selection into the farmer household category with the clusters based on actual income sources earned.

We present various descriptives for both the clusters and self-ascribed status to characterize and compare the various groups. Analysis of variance (ANOVA) was performed to compare mean descriptive values across the livelihood clusters. Tests were adjusted using the Bonferroni method to correct for possible spurious inference due to making multiple comparisons between group means and proportions.

To answer the second research question we asked three open-ended questions on household livelihood aspirations. First, we asked: 'Think about your life right now. What would you like to do more or less of in terms of your income generating activities?' Second, to obtain a better idea of the feasibility of this aspiration we asked: 'What concrete steps have you taken towards achieving the above changes?' Third, and finally, we wanted to assess any differences between current and future aspirations and asked: 'What would you like your children's life to look like in the future?' We compared household aspirations for the two groups described in the previous paragraph (income-based clusters and self-ascribed status). In addition, we disaggregated the analysis between the two districts to compare findings for a district with good agro-ecological potential and market access (Embu) with a district with lower agro-ecological potential and market access (Kitui).

In the discussion, we try to answer the third and final research question by providing targeting suggestions for AR4D interventions based on our findings. We apply the framework developed by Dorward et al. (2009) to describe how household aspirations in various contexts can inform technology development and transfer interventions. We also provide examples of technologies we see as suitable for households as well as suggestions to improve targeting of interventions.

3.3 Results

To what extent are rural households 'really' farmers based on their income portfolio? Table 3.1 shows the contribution of various on- and off-farm income sources to the household income portfolio. We distinguished three sources of on-farm income (crop sales, value of own crop consumption and livestock income) and four sources of off-farm income (non-farm wage labour, farm labour, self-employment / trade and transfers, such as remittances and pensions). Data is presented for the full sample and for the four livelihood clusters. Livelihoods in the study areas were quite diversified, with half of the income coming from either farm- or off-farm activities. Most households (32%) belonged to the mixed income and non-farm (30%) clusters. Full-time farmers (24%), were a minority. Part-time farming is the norm for more than three quarters of the households. Farm-worker households constituted the smallest (10%) cluster. The full-time farmer and non-farm household clusters were the most specialized, with an average 88 or 84 percent of income from farm and off-farm activities, respectively. For all clusters, crop activities contributed more to income than livestock activities, though livestock is evidently also an important asset. Mixed farmers were less market-oriented than full-time farmers, with around half the share of income from crop sales. In fact, with increasing off-farm income marketed shares reduce and farming becomes a source of food rather than income.

Table 3.1 Income by source and livelihood cluster

	Total sample (n=624)	Full-time farmer (n=165)	Mixed income (n=201)	Farm-worker (n=66)	Non-Farm (n=192)
Farm income share (%)	49.0	88.4	53.2	36.0	15.3
Crop sales (%)	17.4	37.6	15.8	12.0	3.7
Value own consumption (%)	19.7	27.9	24.2	17.6	8.6
Livestock income (%)	11.9	23.0	13.3	6.3	3.0
Off-farm income (%)	51.0	11.6	46.8	64.0	84.7
Farm wage labour (%)	8.7	4.8	2.7	57.0	1.7
Non-farm wage labour (%)	25.0	3.3	22.3	2.8	54.0
Self-employment / trade (%)	8.8	1.0	10.2	1.8	16.5
Transfers (%)	8.5	2.5	11.6	2.4	12.5

Do households that we tend to call farmers actually consider themselves to be farmers? Table 3.2 provides a further disaggregation of the livelihood clusters across various household groupings. Though full-time farmers were a minority based on actual income composition, almost three quarters of households self-identified as being a farmer household in 2015. The large majority of full-time farmer and mixed income households ascribed themselves to the farmer household category, but even among farm-worker and non-farm households over sixty percent self-identified as farmer household. Though farm-workers might be expected to identify as farmers (albeit not always on their own farm), this is a surprising result for non-farm households considering that they earned on average only 15 percent of their income from farming in 2013. However, they are generating a considerable amount of food for consumption from their farming activities, which could drive identification into the farmer category. There were significant differences between districts in terms of income sources. The share of full-time farmers in Embu (68%) was considerably higher than in Kitui (32%). By contrast, two-thirds of the non-farm households lived in Kitui. Mixed income and farm-worker households were almost equally divided across the two districts.

Table 3.2 Self-identification and location (district) across livelihood clusters

	Total sample (n=624)	Full-time farmer (n=165)	Mixed income (n =201)	Farm-worker (n=66)	Non-Farm (n=192)
Total sample - clusters (%)	100	26.4	32.2	10.6	30.8
Self-described Farmer (%)	74.0	88.5	75.6	66.7	62.5
Kitui (%)	50.5	31.5	52.2	47.0	66.1
Embu (%)	49.5	68.5	47.8	53.0	33.9

Descriptives presented in Table 3.3 show that there are considerable differences between clusters in both demographics and welfare characteristics. For example, full-time farmers are older than non-farm households, whereas the latter are better educated. There are no significant differences in terms of household size.

Table 3.3 Characteristics of income-based and self-ascribed livelihood clusters and districts

	Total sample (n=624)	Livelihood cluster				Self-perception Farmer household		Location District	
		Full-time farmer (n=165)	Mixed income (n=201)	Farm-worker (n=66)	Non-Farm (n=192)	No	Yes	Kitui	Embu
Demographics and Wealth									
Household size (No.)	4.77	4.69$_{a}$	4.67$_{a}$	4.74$_{a}$	4.94$_{a}$	4.78$_{a}$	4.76$_{a}$	5.27$_{a}$	4.25$_{b}$
Age household head (years)	50.46	54.12$_{a}$	50.53$_{a,b}$	49.11$_{a,b}$	47.69$_{b}$	48.01$_{a}$	51.31$_{b}$	49.45$_{a}$	51.48$_{a}$
Education head (years)	7.56	6.87$_{a}$	7.66$_{a,b}$	6.26$_{a}$	8.51$_{b}$	7.71$_{a}$	7.51$_{a}$	7.87$_{a}$	7.25$_{a}$
Household income (USD PPP)	4,816	4,383$_{a}$	4,129$_{a}$	1,999$_{b}$	6,875$_{c}$	5,264$_{a}$	4,658$_{a}$	4,768$_{a}$	4,864$_{a}$
Income per capita (USD PPP)	1,197	1,071$_{a}$	1,092$_{a}$	490$_{b}$	1,660$_{c}$	1,329$_{a}$	1,151$_{a}$	1,064$_{a}$	1,334$_{b}$
Poverty - < USD 1.49 PPP (yes=1)	.40	.45$_{a}$	.38$_{a}$	.76$_{b}$	.24$_{c}$	.38$_{a}$	.40$_{a}$	.44$_{a}$	.35$_{b}$
Current asset value (USD PPP)	1,816	1,434$_{a}$	1,724$_{a,b}$	680$_{a}$	2,630$_{b}$	2,484$_{a}$	1,582$_{b}$	2,002$_{a}$	1,626$_{a}$
Land owned (ha)	.95	1.01$_{a}$	1.00$_{a}$	.59$_{a}$	.97$_{a}$	.98$_{a}$	.94$_{a}$	1.19$_{a}$	.71$_{b}$
Tropical livestock units (No.)	1.74	1.99$_{a}$	1.95$_{a}$	.87$_{b}$	1.62$_{a,b}$	1.63$_{a}$	1.78$_{a}$	2.08$_{a}$	1.40$_{b}$
Farm returns and input use									
Returns to land (income / ha)	3,798	6,100$_{a}$	4,079$_{b}$	2,021$_{b,c}$	2,137$_{c}$	2,797$_{a}$	4,149$_{b}$	2,370$_{a}$	5,254$_{b}$
Returns needed (USD / ha PPP)	6,023	4,588$_{a}$	5,656$_{a}$	9,624$_{b}$	6,418$_{a,b}$	6,812$_{a}$	5,747$_{a}$	5,804$_{a}$	6,246$_{a}$
Returns gap (USD PPP)	-2,222	1,512$_{a}$	-1,574$_{b}$	-7,609$_{c}$	-4,281$_{c}$	-4,020$_{a}$	-1,594$_{b}$	-3,434$_{a}$	-987$_{b}$
Farm family labour (person days)	177.7	206.6$_{a}$	191.2$_{a}$	124.4$_{b}$	157.0$_{b}$	148.5$_{a}$	187.9$_{b}$	13.9$_{a}$	23.1$_{b}$
Farm hired labour (person days)	43.4	48.2$_{a,b}$	33.9$_{a,b}$	11.9$_{a}$	60.2$_{b}$	50.1$_{a}$	41.1$_{a}$	194.5$_{a}$	160.5$_{b}$
Chemical fertiliser (kg/ha)	106	159$_{a}$	90$_{b}$	69$_{b}$	89$_{b}$	62$_{a}$	121$_{b}$	47.9$_{a}$	38.9$_{a}$

Note: Values in the same row and sub-table not sharing the same subscript are significantly different at $p< 0.05$ in the two-sided test of equality for column means. Tests assume equal variances.

Non-farm households are relatively wealthier, with significantly higher incomes, lower poverty rates and more assets than the other clusters. Interestingly, land ownership does not differ significantly. This may be caused by the larger share of non-farm households in Kitui where landholdings are larger. An alternative explanation could be that non-farm households did not step out of farming all together, but added non-farm activities to their income portfolio. Farm-workers are clearly the most disadvantaged group. They have by far the lowest incomes and 74 percent lives below the poverty line. Differences between self-ascribed farmer- and other households are less pronounced, with farmer households having older heads and fewer assets. Despite larger land sizes, households in Kitui earned less income per capita. This is partly related to the larger household sizes in the district as total income does not differ significantly.

Table 3.3 also provides information on farm returns, accounting for relevant crop and livestock input costs and use. In addition, we computed the returns from farming needed to raise a particular household above the poverty line given family size and cultivated land.[3] By deducting returns needed from actual returns we gain an idea of the ability to generate sufficient returns from agriculture to move above the poverty line. The analysis shows that full-time farmers have the highest actual returns while they require lower returns to stay out of poverty given their household size and land holdings. Accordingly, they are the only category with a positive gap, i.e., their agricultural income alone takes them above the per capita poverty line. Full-time farmers and mixed income households utilize more family labour, while non-farm households are more reliant on hired labour. Farm-workers have the largest gap of all groups and show limited use of both hired and family labour. Chemical fertiliser use is considerably higher among full-time farmers, indicating that they are more intensified. Similar to full-time farmers, self-ascribed farmer households use more chemicals and use more family labour for farming. Returns to farming are also higher for self-ascribed farmer households, translating into a smaller gap than that for households not describing themselves as farmers. This suggests that households identifying as farmers may be more inclined to invest in agricultural activities, even though these are not always the most important income sources.

Farm returns to land and labour in Embu are considerably higher than in Kitui. This is probably a result of the difference in agro-ecological potential between the two districts. The greater use of chemical fertiliser in Embu also indicates a more intensified agricultural system compared with Kitui. Finally, there is also a higher proportion of full-time farmers in Embu who realize higher returns per hectare. This suggests that the larger share of full-time farmers in Embu is supported by higher returns, whereas rural households in Kitui may be forced out of farming into off-farm activities to support their families. However, it could also indicate that households in Kitui have better opportunities for off-farm employment and thus choose not to focus on farming.

There is significant heterogeneity among the different groups of households based on their

[3] Returns in $/ha/year needed are: ($1.49 * family size * 365) / cultivated area (Harris & Orr, 2014).

income portfolio and potential. Furthermore, there is a clear inconsistency between their self-perception and their actual income portfolio. However, it is impossible to judge, from the current income portfolios, what the reasons are for the less intensive and lower performance in farming. Lower ability to invest or lack of skills could be one explanation, but it could also reflect a choice by the household to focus more on off-farm opportunities and thereby lower their level of inputs (cash and labour) into farming. To shed light on this question, we utilized aspiration based questions to understand household interest in farming which could be one determinant of the effort they put into their farming activities.

What are household livelihood aspirations and are there differences based on self-perception or opportunities such as agro-ecological potential or proximity to markets? Table 3.4 provides an overview of livelihood aspirations to increase farm- and/or off-farm income. This is based on open questions with respondents' answers categorized and coded as farm- or off-farm. In line with their self-identification, the majority of households (64%) aspire to increase their farm income. Farm aspirations include irrigation, purchasing land, expanding cash and horticultural crops, planting (fruit) trees as well as expanding or starting dairy and poultry farming. Examples of answers include: 'I would like to commercialize crop farming by buying a water pump and get a big tank to enable irrigation.' Or: 'Intensify our farming activities through planting mango trees as an enterprise.' And: 'Advance crop farming by shifting from manual to intensive farming equipment, like greenhouses.' Considerably fewer households (31%) aspire to increase their off-farm income. Off-farm aspirations comprised advancing current- or starting new businesses, including shops, salons, transportation and rental houses. Examples of respondent aspirations include: 'Starting a hardware business and m-pesa[4] shop in the locality because there is a vacuum.' Or: 'I would like to invest more in business, such as a shop, expand my butchery and buy a motorcycle for transport business.' And: 'Starting a boutique and shoe selling business.'

Table 3.4 Livelihood aspirations and steps taken to accomplish them by household grouping

		Aspiration		Steps taken	
		Farm (yes=1)	Off-farm (yes=1)	Farm (yes=1)	Off-farm (yes=1)
Total sample		.64	.41	.37	.20
Livelihood cluster	Full-time farmer	$.65_{a}$	$.31_{a}$	$.36_{a}$	$.13_{a}$
	Mixed income	$.69_{a}$	$.39_{a,b}$	$.42_{a}$	$.21_{a,b}$
	Farm-worker	$.56_{a}$	$.47_{a,b}$	$.24_{a}$	$.18_{a,b}$
	Non-Farm	$.60_{a}$	$.48_{b}$	$.39_{a}$	$.26_{b}$
Farmer household	No	$.47_{a}$	$.57_{a}$	$.27_{a}$	$.30_{a}$
	Yes	$.70_{b}$	$.35_{b}$	$.41_{b}$	$.17_{b}$
District	Kitui	$.64_{a}$	$.49_{a}$	$.47_{a}$	$.27_{a}$
	Embu	$.63_{a}$	$.32_{b}$	$.28_{b}$	$.13_{b}$

Note: Values in the same column and sub-table not sharing the same subscript are significantly different at p< .05 in the two-sided test of equality for column means. Tests assume equal variances. Households can aspire to increase only farm or off-farm, increase both or increase neither income source. Accordingly, the percentages presented in the table can overlap and need not add up to one hundred percent.

[4] M-Pesa is the Kenyan mobile money platform.

The more common aspiration to increase farm income was also reflected in the percentage of households that had taken steps towards that increase (37% in farming and 20% for off-farm incomes). Aspirations to increase farm income did not differ significantly between livelihood clusters. However, non-farm households more often aspire to increase their off-farm income compared to full-time farmers. Similarly, non-farm households more often took steps to increase their off-farm income. Self-ascribed farmer households were more likely to aspire to increases in their farm income and less likely to aspire to increases in off-farm income. This confirms the assumption that there is a link between self-perception and aspirations / steps taken by households, which needs to be further explored. In Embu, households were less likely to have taken steps to accomplish their aspirations. Comparing aspirations between districts shows no differences for farm aspirations, whereas more households in Kitui aspire to increase off-farm income.

Finally, we asked households to describe how they would see the future for their children (Table 3.5). This was again an open question whereby we coded answer categories that are not mutually exclusive. Our aim here was to get more insights into longer term aspirations by further detaching answers from the respondents' immediate needs and short term plans.

Table 3.5 Future aspirations for children by various household groupings

	Total sample (n=624)	Livelihood cluster				Self-perception		Location	
		Full-time farmer (n=165)	Mixed income (n=201)	Farm-worker (n=66)	Non-Farm (n=192)	Farmer household		District	
						No	Yes	Kitui	Embu
Farming (yes=1)	.06	$.07_a$	$.08_a$	$.03_a$	$.08_a$	$.06_a$	$.06_a$	$.07_a$	$.05_a$
Business (yes=1)	.23	$.25_a$	$.23_a$	$.22_a$	$.21_a$	$.18_a$	$.24_a$	$.24_a$	$.21_a$
Wage labour (yes=1)	.57	$.58_a$	$.65_a$	$.60_a$	$.51_a$	$.57_a$	$.57_a$	$.56_a$	$.59_a$
Education (yes=1)	.53	$.54_a$	$.55_a$	$.56_a$	$.48_a$	$.53_a$	$.53_a$	$.54_a$	$.52_a$

Note: Values in the same column and sub-table not sharing the same subscript are significantly different at $p< .05$ in the two-sided test of equality for column means. Tests assume equal variances. Households can aspire to increase only farm or off-farm, increase both or increase neither income source. Accordingly, the percentages presented in the table can overlap and need not add up to one hundred percent.

Besides general comments that parents wished their children to have a good life we could distinguish the following aspiration categories: farming, business, non-farm wage labour and education. The business and wage labour categories, and to some extent education, can be interpreted as parents hoping for a non-farm career for their children. Common aspirations include: 'I would like them to become educated people with good jobs' and 'Live healthy, get education, have good jobs and own businesses.' Only 6% of households across all groups aspired a future in farming for their children. Usually this was combined with off-farm aspirations, for instance: 'Having good jobs and also being professional farmers.' Only nine respondents (1.5%) wished their children to focus exclusively on farming (not depicted in the table). These respondents wanted their children to engage in intensive farming, for example, wishing they would become 'prominent farmers with dairy cattle and large scale poultry and fruit farming.’ Three respondents even explicitly hoped that their children would ‘not be farmers’. In sum, most households aspire to increase their current farm income, yet they hope for a different future for their children.

3.4 Discussion

How can we better understand the complex rural livelihood decision environment in order to improve targeting of interventions towards the most appropriate households and support their needs more effectively? In order to answer this question we build on the framework of livelihood aspirations and strategies of the poor developed by Dorward et al. (2009). Their analysis is built on the proposition that people want to maintain and/or advance their current welfare and that they attempt to do this by expanding existing activities and/or moving into new activities. From this they identify three broad types of rural livelihood strategies for farming households: (1) ‘Hanging in’, where households engage in agricultural activities to maintain their current livelihood, often in the face of adverse socio-economic circumstances and few or no other options to improve their situation; (2) ‘Stepping up’, where investments are made to improve agricultural returns to improve livelihoods; (3) ‘Stepping out’, accumulated assets are used to move into non-agricultural activities with higher or more stable returns. This may, but need not, involve cessation of all farming activities. This group could even be subdivided into a fourth category – ‘stepping out while staying put’ whereby people stay on the land while concentrating on off-farm opportunities. In this case it may be that the land is perceived as a long-term safety net in case of job loss, business failure or for retirement, or it could be that they identify culturally as ‘farmers’ and do not want to give that up. This situation has implications for the development of rural areas as it hinders the consolidation of land which would enable the ‘stepping up’ group to expand and grow their business.

Dorward et al., (2009) also identify situations where these strategies are likely to be more or less important, distinguishing between poor and less-poor households as well as high- and low potential contexts. We adapted their approach by explicitly differentiating between on- and off-farm household aspirations and poor and less poor households (see Table 3.6). We recognize that the poverty line is somewhat arbitrary but use it for illustrative purposes only. This differentiation on the basis of the total household income has been chosen to account for differences in investment potential. Poorer households will have less disposable income to make investments in farming or other businesses. We believe that taking household aspirations into account will improve the likelihood of response to or uptake of innovations, as households will look for opportunities that support their aspirations. We envisage that less-poor households with aspirations in agriculture will aim to step up as they can afford to invest, while ‘hanging in’ is often the only option for poor households. Less-poor households with off-farm aspirations are likely to step out by migrating or starting local businesses, whereas poorer households are likely to hang in while engaging in farm labour or small local business activities such as roadside kiosks. Obviously, differentiating by livelihood strategy is only the first step when targeting rural households, though it is an important and often overlooked one. For agricultural interventions, the second step will have to account for the agro-ecological potential of the region in question. However, we believe that there are technologies and options available for almost all regions. Moreover, this aspect of targeting is well established while the first step of accounting for aspirations has often been neglected.

Table 3.6 Implications for AR4D of investment potential and household aspiration

	Aspiration					
	Agriculture (% of sample)			Off-farm (% of sample)		
	Likely pathway	AR4D role	Characteristics of potential technologies	Likely pathway	AR4D role	Characteristics of potential technologies
Higher potential to invest (less poor / >1.49$)	Stepping up	High	High yielding, input and capital intensive, marketable	Stepping out	Very low	Business incubation for agricultural enterprises
	40%			23%		
Lower potential to invest (very poor / <1.49$)	Hanging in / slowly stepping up	High	Lower risk, labour intensive, moderate / low capital intensive	Hanging in / slowly stepping out	low	Low input / labour demands and low risk
	24%			18%		
Total	64%			41%		

Based on the likely livelihood strategies, Table 3.6 provides an overview of the households that can be targeted effectively by agricultural interventions. First, agricultural interventions are obviously relevant for households that aspire to intensify their agricultural portfolio; this is 64 percent of the sample. While this is the majority, it may appear surprisingly low for some people as the sample represents rural households that all engage in farming activities. Of the 41 percent that aspire to increase off-farm activities, only households with both on- and off-farm aspirations (9% not shown in the table) would be additional obvious targets.

Households aspiring to increase their agricultural income should be the main target group of agricultural interventions, as they are more likely to be interested in innovations and respond to incentives. Having said that, provision of attractive incentives for agriculture could persuade other households to re-assess their priorities. Characteristics of suitable technologies will differ by agro-ecological context and a household's potential to invest. Households that have the ambition to make their farm an enterprise and have some capital to invest can be served by catering to their needs. For example, less poor households may have the capacity to invest in options such as irrigation facilities, more expensive livestock breeds for dairy production or on-farm processing facilities. Yet, the poorer segment of the population with ambitions in agriculture are less likely to have funds to invest in farming and thus need a different set of technologies. One avenue could be more labour intensive options that reduce their downside risk while gradually improving their revenues. In this category, we would see agronomic management options such as agroforestry, deep tillage, small ruminants, poultry or zebu cattle. For the poorest, social protection programs or cash transfers may be required to keep households from falling back and enable them to start stepping up.

Some households aim to step completely out of agriculture by migrating to cities or specializing into non-farm rural activities (Dorward et al., 2009). At first glance, these households should not be the primary target group for agricultural interventions. To assist this group one has to carefully assess the goals they pursue with their agricultural portfolio. There are two very different options. First, they might invest in agriculture in order to generate revenue to invest in their off-farm endeavours. Second, they might use farming as a safety net and produce purely for home consumption with limited sales. In the first case they will require technologies that are easily marketable, may require investments in inputs but possibly less labour, e.g., modern hybrid varieties that might need pesticides or fertiliser to reach their high yield potential. In the second case, the household is likely to be unwilling to invest in farming (neither cash nor labour) and will demand technologies that provide stable outputs in low input regimes such as medium yielding, pest and disease tolerant non-hybrid (replantable) varieties. It is critically important to carefully consider this group from a societal point of view. If, as elaborated above, this group is not willing or able to fully step out and enable the 'stepping up' group to accumulate land, the rural transformation process as envisioned in the combination of 'stepping-up' and 'stepping-out' will likely not work. The population remaining in the rural areas will then be trapped on small land parcels and remain vulnerable to shocks and poverty. Therefore, enabling this group to pursue their aspiration to step out could have secondary effects for the 'stepping up' group to enable the rural transformation.

Targeting agricultural interventions should be differentiated by household aspirations as well as on agro-ecological grounds. However, it may be very difficult to identify households and their preferred pathways as many rural households will identify themselves as farmers, especially when agricultural researchers are asking. Prospects of free inputs, training and other, more nebulous, project-related benefits may incentivise households to overstate the importance of agriculture. Indeed, in our exercise more households identified as farmers than expected based on their income portfolio. This may have been influenced by expectations of future support for respondents who are identified as farmers. Another explanation for the high share of self-identified farmer households may be related to culture and social norms in communities where farming is seen as a way of life. Finally, the off-farm activities that households engage in are diverse and farming could still be an important contributor to household income. Furthermore, across all groups farming contributes to home consumption needs and therefore food security which has to be carefully considered.

Rural households do have aspirations but their livelihood strategies are based on current circumstances and qualifications. For example, aspirations were often related to 'continuing' or 'expanding' current activities, such as renting in land, investing in the current business, etc. It may be that a stepping-up livelihood strategy is deemed less risky and more feasible than stepping-out of farming. Though many respondents self-identified as farming households, very few aspired to a future for their children in farming. Respondents thus seem to be aware that stepping-out may not be possible for them due to educational and other barriers. Indeed, it is less likely for a middle-aged person to make the transition out of agriculture, while it may be possible for their children. The difference in livelihood strategies for respondents, which is most often stepping up, and their children, which is almost exclusively stepping out, is likely to be a product of both household aspirations and realities. This reflects long term trajectories whereby parents see their stepping up as eventually enabling their children to step out.

3.5 Conclusions

Our findings highlight the importance of carefully distinguishing between different types of rural households. This distinction must go beyond farming and non-farming households, by further accounting for differences within income portfolios but also aspirations. Avoiding the trap of calling all households with farm activity ‘farmers’ and assuming they have no other interests, may increase the match between demands and technology development. Considering non-farm aspirations in rural contexts is clearly important; they may influence household perceptions of the relative value of agricultural innovations and hence their choice to adopt – or not.

Very few parents hope for a future in farming for their children. This is in stark contrast to their personal aspirations and investment plans, which mostly involve expansion or intensification of farming. This finding raises several pertinent questions that should be explored in future research. For example, what is the implication for agricultural innovations now and in the future? If most households foresee their children stepping out, does this mean that they are focused on short-term investments with quick wins? Though all poor households are probably looking for quick wins, this may mean that even wealthier households might not have the long-term horizons needed to consider investments in practices with delayed benefits such as agroforestry or soil fertility management.

There are also implications for changes in land use patterns, currently characterized by high levels of land fragmentation in densely populated areas. If households increasingly step out of farming, would this reverse the trend and enable consolidation of land for the next generation, e.g., through people selling / renting out their land? Or is the cultural attachment to land too strong and will agricultural areas become increasingly fragmented into smaller plots unable to produce excess food for sale to feed a burgeoning population? Are safety nets sufficiently developed to enable households to leave their farms or is land still perceived as a necessary insurance or for retirement? Where are the opportunities outside farming to support increasing numbers of people leaving agriculture?

Finally, what are the implications for agricultural research and global development goals? How realistic is a win-win strategy of ending hunger and poverty by improving the productivity of the poor through agricultural innovations? Could it be better to tailor agricultural technologies to less-poor full-time farmer households with potential for more efficient larger scale production? But what about food security of the poorest with limited alternatives?

These complicated questions are largely derived from people’s answers to two simple questions: What are your current investment plans? And, what would you like your children’s life to look like in the future? This paper is meant to start a discussion around the complicated issues raised by our simple questions. We do not claim to understand this complex system fully or that these are the right questions to answer. However, we do hope that raising these issues will broaden peoples' understanding of rural realities. Specifically, we hope that the agricultural research for development sector will more actively consider the implications of rural household diversity and aspirations for research and interventions. We therefore urge the field to listen better to those people we call 'farmers' in order to offer solutions that meet their aspirations and realities.

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Chapter 4
A recipe for success?
Learning from the rapid adoption of improved chickpea varieties in Ethiopia

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Abstract

Many studies focus on the constraints faced by smallholder farmers in order to explain the limited adoption of new technologies in sub-Saharan Africa. By contrast, we study the conditions that led to the remarkable and rapid spread of improved chickpea varieties in Ethiopia: from 30 to 80% of the farmers in just seven years. A combination of factors explained this rapid uptake. First, compared with local varieties, superior returns and disease resistance ensured that the technology was attractive to farmers. Second, chickpea was already an important crop for rural households in the studied districts, for both cash income and consumption. Finally, the region where the improved varieties were introduced had good market access. In sum, an attractive technology suitable for rural households in a conducive environment enabled adoption. We appeal to improve agricultural development interventions by paying greater ex-ante attention to potential factors of success and failure. This should ensure that agricultural innovations fit the realities and demands of rural households to ultimately design and deploy more successful interventions.

4.1 Introduction

Agricultural development is critical for sustained poverty reduction in sub-Saharan Africa (Dercon et al., 2009; World Bank, 2007). Activities designed to address the vulnerability of the African rural poor often promote agricultural innovations to increase productivity, efficiency and ultimately income (Parvan, 2011). Yet technology transfer and uptake by African smallholders has progressed slowly (van Rijn et al., 2012a; Walker & Alwang, 2015). Indeed, the weak adoption of agricultural technologies in sub-Saharan Africa is a well-documented and widely cited reason for lack of improvement in agricultural productivity (Headey & Jayne, 2014; World Bank, 2015c). At the same time there is increasing pressure to demonstrate impact, success and 'value for money' of agricultural research (Sumberg et al., 2012). A major research topic is therefore why agricultural innovations that appear to be beneficial are not widely adopted by smallholders (Zilberman et al., 2012).

Smallholder farmers face numerous barriers and constraints that help to explain the limited adoption of new technologies in sub-Saharan Africa (Woittiez et al., 2015). Following the seminal study of Feder et al. (1985), (under-)adoption is often explained in relation to farm size (Headey & Jayne, 2014; Josephson et al., 2014), risk preferences (Dercon & Christiaensen, 2011; Wossen et al., 2015), human capital (Liu & Yamauchi, 2014), labour availability (Jayne et al., 2014; Ndlovu et al., 2014), credit constraints (Holden & Lunduka, 2013), land tenure (Beekman & Bulte, 2012; Jin & Jayne, 2013; Melesse & Bulte, 2015), access to input and output markets (Jack, 2011; Jayne et al., 2010) or a combination of the above (Wakeyo & Gardebroek, 2013). Nonetheless, there is little coherent understanding of technological change in smallholder African agriculture (Glover et al., 2016). Moreover, the large diversity within and among smallholder farming systems affects the uptake of technologies (Franke et al., 2014; Giller et al., 2011). For crops to be adopted and have an impact, they should be equal or superior to conventional varieties (De Groote et al., 2016). The paucity of studies that document the net returns to promising technologies thus constitutes a surprising gap in the literature (Foster & Rosenzweig, 2010). Sumberg (2005) rightly indicates that for agricultural researchers to suggest that their innovations are not adopted because of well-known constraints is to deny their role in and responsibility for the agricultural research for development process.

Instead of focusing on the lack of adoption, we studied the dramatic increase in cultivation of improved chickpea varieties in Ethiopia: from 30 to 80% of farm households in just seven years. Improved chickpea varieties are said to be a key pro-poor and environmentally friendly technology (Kassie et al., 2009). However, environmentally sustainable technologies have to simultaneously generate positive economic benefits if they are to achieve wide adoption (Lee, 2005). Grain legumes such as chickpea are both cash and food crops, providing key components of a healthy diet, including proteins and minerals, while helping to reduce pest and disease build-up associated with cereal mono-cropping and enhancing nitrogen availability for subsequent crops (Franke et al., 2014). Using three rounds of panel data we seek to understand what drove the rapid adoption of improved chickpea in Ethiopia? To answer our research question we formulated three questions:

1) What is the extent of adoption of improved chickpea varieties in the study area?
2) What were the main determinants of improved chickpea adoption?
3) Are economic returns to improved chickpea good predictors of adoption?

Verkaart et al. (2017a) used the same data and found that improved chickpea adoption significantly increases household income while also reducing household poverty. In this paper we explore the determinants of adoption that enabled this success. Improved chickpea varieties became available only relatively recently in the study area and can be clearly distinguished from local varieties based on seed colour and size. This allowed us to capture adoption accurately and study the mechanisms behind the increase in uptake by farmers with limited misattribution. In addition, we move beyond dichotomous static conceptions of adoption by capturing adoption intensity, dis-adoption and comparing chickpea types, varieties and other crops within the farming system. Finally, we move beyond a narrow focus on adoption constraints, which is often used to explain the under-adoption of innovations.

4.2 Background: Chickpea in Ethiopia

Ethiopia presents important challenges in agricultural development (Dercon et al., 2012; Spielman et al., 2010): it is among the poorest countries in the world, highly drought-prone and its agricultural sector accounts for 85% of employment. Ethiopia has a population of 92 million that is expected to grow to 160 million by 2050 (Josephson et al., 2014). As a result, farm sizes declined rapidly, which increased the need for agricultural intensification (Headey et al., 2014). Growth in agriculture is deemed crucial for poverty reduction and food security (Ali et al., 2011). Accordingly, the Ethiopian government placed agriculture at the centre of its growth strategy (Krishnan & Patnam, 2013), with improved productivity of smallholder agriculture a policy priority (Abebaw & Haile, 2013). Surprisingly, there has been little detailed analysis of the impact of investments in agriculture in Ethiopia (Abro et al., 2014; Dercon et al., 2009; Spielman et al., 2010).

Chickpea is an important crop in Ethiopia, ranking seventh in the world and accounting for over 90% of chickpea production in sub-Saharan Africa (Kassie et al., 2009; Pachico, 2014). Both seed types of chickpea are grown: (i) Desi varieties that have brown-reddish small seeds, and; (ii) Kabuli types which have cream coloured larger seeds (Wood et al., 2011). Despite Ethiopia's suitable agro-climatic conditions for both types, traditionally only Desi chickpea was cultivated. International markets favour the Kabuli types which fetch higher prices (Shiferaw et al., 2007). This has attracted attention and steps have been taken to increase Kabuli production and export in Ethiopia (Abera, 2010).

The competitiveness of Ethiopia's chickpea sector depends on improving productivity and enhancing grain quality to provide a consistent supply of the required volumes at competitive prices (Abera, 2010; Keneni et al., 2011). More than ten improved varieties of Desi and Kabuli type chickpea have been released (Asfaw et al., 2012). These varieties have various attributes such as improved yield, grain quality and disease resistance (Dadi et al., 2005; Keneni et al., 2011). At the beginning of our study period the seed system for Kabuli chickpea production in Ethiopia was in its infancy (Jones et al., 2006). Limited seed access prevented interested farmers from planting improved varieties (Asfaw et al., 2011). In 2001 less than 1% of the total chickpea area in Ethiopia was covered by improved varieties (Asfaw et al., 2010), which increased to around 18% of farmers in 2003 (Dadi et al., 2005).

In 2004, initiatives were started to accelerate the adoption of improved chickpea varieties in Ethiopia. The Ethiopian Institute of Agricultural Research (EIAR) cultivated partnerships with major actors along the value chain (Abate et al., 2011). Primary co-operatives received breeder seed for multiplication through contracts to enable the dissemination of improved chickpea varieties (Shiferaw et al., 2007). Moreover, the Tropical Legumes II (TLII)[5] programme supported the establishment of seed grower associations. TLII focused on major chickpea producing areas in the Shewa region for the upscaling of suitable chickpea varieties and marketing strategies (Monyo & Varshney, 2016). Other developments that boosted the chickpea sector were the decision to include chickpea in the Ethiopian Commodity Exchange and formation of the multi-stakeholder EthioPEA alliance.

4.3 Materials and methods

4.3.1 Surveys and data

The districts Minjar-Shenkora, Gimbichu and Lume-Ejere were selected which have a suitable agro-ecology and are major chickpea growing areas (Asfaw et al., 2011). The districts are in the Shewa region north east of Debre Zeit which is 50 km from Addis Ababa. The study area is located in the central highlands at an elevation ranging from 1,900-2,700 meters above sea level. Debre Zeit Agricultural Research Centre (DZARC) is located in the area and is a source of information and improved varieties (Asfaw et al., 2012).

We utilized three rounds of panel data collected under the TLII project. Farm households were randomly selected and thus non-chickpea growing farmers were also interviewed. During the three survey rounds 700, 661 and 631 households were surveyed in 2006/07, 2009/10 and 2013/14 respectively. We limit our analysis to households that were interviewed in all three rounds of the survey, providing a balanced sample of 606 households and attrition rate of 13%. To check for non-random attrition, we compared characteristics in the 2006/07 season and found no significant differences. To enable comparisons across time, we deflated nominal Ethiopian Birr values to real values using the national consumer price index with 2005 as a base following Bezu et al. (2012). These constant 2005 data were subsequently converted from Ethiopian Birr to US dollar (USD) Purchasing Power Parity (PPP) values using rates extrapolated from the 2011 International Comparison Program (World Bank, 2015b).

Adopters are defined as households who planted an improved chickpea variety in the season surveyed. We account explicitly for input and hired labour costs as well as family labour in our analysis of returns and chickpea productivity. To investigate results emerging from the panel data, focus group discussions (FGDs) and semi-structured interviews with experts were

[5] Tropical Legumes II was funded by the Bill & Melinda Gates Foundation to enhance grain legume productivity and production to increase poor farmers' income in drought-prone areas of sub-Saharan Africa and South Asia.

conducted in October 2015. Six villages were purposefully selected to reflect differences in market access, low and high adoption rates as well as variations in wealth. A total of seventy-one farmers participated in the FGDs.

4.3.2 Analysis

Glover et al. (2016) call to move beyond a 'black box' conception of adoption as a dichotomous linear process whereby inferior existing material is replaced by a discrete new technology. Indeed, for innovations such as a new variety, a decision is made regarding the intensity of adoption (Marra et al., 2003; Sumberg, 2016). It is therefore important to consider how much land is allocated to new varieties compared with other (local) varieties and other crops. We assess various indicators of adoption of the various improved chickpea varieties and types (Question one). Specifically, we analyse the share of households as well as land (in hectare and percentage) allocated to (improved / local) chickpea and other crops. We also provide information on which improved chickpea varieties were adopted and their characteristics.

We assess the determinants of technology adoption (Question two) by comparing descriptive statistics related to the technology, household characteristics and the context of adopters and non-adopters. We assess differences in returns to improved and local chickpeas and compare yields, costs, labour and prices of improved and local chickpeas with other major cereals and legumes using analysis of variance (ANOVA). We also compare demographics, income, poverty, asset ownership and livelihoods as well as contextual differences in terms of market and extension access, rainfall, elevation and soil type. Where we do not have data we supplement results with findings from the FGDs and literature. Finally, we performed an in-depth analysis of the returns to improved chickpea adoption to assess its value as a determinant for adoption (Question three).

Because improved chickpea varieties have not been distributed randomly, adopters and non-adopters may differ systematically (Asfaw et al., 2011). This raises concerns of selection bias, e.g., where better-skilled farmers are more likely to adopt or if such individuals are targeted by technology transfer (Dercon et al., 2009). Indeed, Smale and Mason (2014) found that adopters are generally wealthier in terms of capital and asset endowments and have better access to information, financial services, markets and infrastructure. Therefore, the decision to grow improved varieties is potentially endogenous on household welfare. An advantage of panel data over cross-sectional data is that observed and unobserved time-invariant household characteristics can be separated (Dercon et al., 2009). We utilize fixed effects estimation and further control for time-invariant unobservables by including village time interactions. For a rigorous assessment of the impact of improved chickpea adoption on income and poverty we refer to Verkaart et al., (2017), where instrumental variable fixed effect models have been applied to the same dataset. We included various covariates in our yield and gross chickpea estimations to control for input costs including family labour. Disaggregated results are presented for Kabuli, improved Desi and local Desi types and by specific chickpea varieties.

4.4 Results and discussion

4.4.1 Adoption of improved chickpea varieties

First we address the question: *What is the extent of adoption of improved chickpea varieties in the study area?* In the 2006/07 season a little more than 30% of the farmers grew improved chickpea varieties while over half of them produced local Desi varieties (Table 4.1). Between 2006/07 and 2013/14 adoption of improved chickpea increased dramatically to 79% of households, representing almost 19% of total cultivated area and 85% of the chickpea area. In addition, more farmers started cultivating chickpea, with 90% of chickpea growers adopting improved varieties in the 2013/14 season. In terms of number of growers and allocated area, chickpea was the third most important crop and the most important legume. Varieties adopted were mainly of the Kabuli type and particularly substituted local Desi and to some extent wheat, maize and other legumes such as grass pea (*Lathyrus sativus* L.) and field pea (*Pisum sativum* L.). Only 5% of farmers adopted improved Desi varieties. The dramatic increase in improved adoption of Kabuli varieties was largely driven by adoption among former Desi growers and farmers that had not previously grown chickpea.

Table 4.1 chickpea adoption and planting of other crops

	Planting of crops (%)			Land allocation (ha)			Land allocation (%)		
Crop	06/07	09/10	13/14	06/07	09/10	13/14	06/07	09/10	13/14
Improved chickpea	31.2	63.0	79.0	0.17	0.33	0.42	5.9	12.1	18.9
Improved Kabuli	30.5	56.9	73.4	0.17	0.30	0.40	5.6	10.9	17.6
Improved Desi	2.0	7.3	5.6	0.01	0.03	0.03	0.3	1.2	1.3
Local Desi	52.8	47.9	25.7	0.22	0.15	0.09	8.9	5.9	3.4
Chickpea	65.5	80.5	88.1	0.39	0.48	0.51	14.8	18.0	22.4
Teff	90.9	94.9	97.2	0.73	0.74	0.74	31.5	29.2	33.4
Wheat	94.7	95.2	93.2	0.80	0.86	0.63	35.0	34.2	28.4
Barley	39.8	37.3	32.1	0.09	0.08	0.07	3.9	3.4	3.0
Maize	26.4	15.8	8.4	0.03	0.04	0.01	1.4	1.2	0.6
Sorghum	4.3	2.5	0.3	0.02	0.02	0.00	1.0	0.5	0.0
Lentil	35.8	53.0	44.5	0.06	0.08	0.07	5.5	7.3	6.7
Faba bean	33.7	39.3	36.4	0.14	0.20	0.17	2.7	3.4	3.3
Grass pea	21.8	19.5	10.3	0.06	0.04	0.02	2.6	1.8	0.9
Field pea	18.2	13.2	10.8	0.04	0.03	0.03	1.6	1.0	1.0
Observations		606			606			606	

Among the improved varieties, Arerti was the most popular, followed by Shasho and (initially) Ejere: all Kabuli types (Table 4.2). Improved Desi varieties released in the late 70s and early 80s and the more recently introduced Kabuli varieties, Chefe and Habru, were adopted by few farmers. The varieties Arerti and Shasho have the greatest yield potential combined with tolerance to *Fusarium* wilt. A clear advantage of Arerti is its additional tolerance to *Ascochyta* blight. Both diseases are major problems for chickpea production in Ethiopia (Abate, 2012). During FGDs farmers indicated that they preferred Arerti because of its tolerance to these fungal diseases.

A majority of people in Lume-Ejere were already growing improved chickpea in 2006/2007 (52%) and in 2013/2014 almost all households had adopted the new varieties (91%) (Figure 6.1). In Minjar-Shenkora, only few households grew improved chickpea (12%) in the

2006/07 season but by the end of the study the majority of farmers had adopted (84%). Gimbichu had some initial adopters (22%) but saw a relatively limited increase in adoption to less than half of the farmers (45%).

Table 4.2 Chickpea variety information

Chickpea variety	Households planted (%) 06/07	09/10	13/14	Type	Year released	Yield (t/ha)	Seed size (mm)	Maturity (days)
Arerti	7.8	19.3	50.3	Kabuli	1999	1.6 - 5.2	6	105 - 155
Shasho	14.5	38.6	22.9	Kabuli	1999	1.6 - 4.6	6 - 7	90 - 155
Ejere	12.7	0.2	0.0	Kabuli	2005	unknown	8 - 9	unknown
Dubi	0.7	5.8	5.3	Desi	1978	1.7 - 2.8	5 - 6	110 - 115
Habru	0.0	2.8	5.5	Kabuli	2004	unknown	unknown	91 - 140
Chefe	1.0	0.8	0.3	Kabuli	2004	1.2 - 4.8	6	95 - 150
Marye	0.2	0.3	0.3	Desi	1986	1.8 - 3.0	5 - 6	106 - 120

Chickpea variety	Tolerance / special trait	Origin
Arerti	Ascochyta blight, Fusarium wilt	ICARDA
Shasho	Fusarium wilt	ICRISAT
Ejere	Ascochyta blight, drought	ICARDA
Dubi	Bold seed size	DZARC
Habru	Ascochyta blight, drought	ICARDA
Chefe	Fusarium wilt, Short duration	ICRISAT
Marye	Moisture stress	ICRISAT

Note: Debre Zeit Agricultural Research Center (DZARC), International Center for Agricultural Research in the Dry Area (ICARDA); International Crops Research Institute for the Semi-Arid Tropics (ICRISAT).

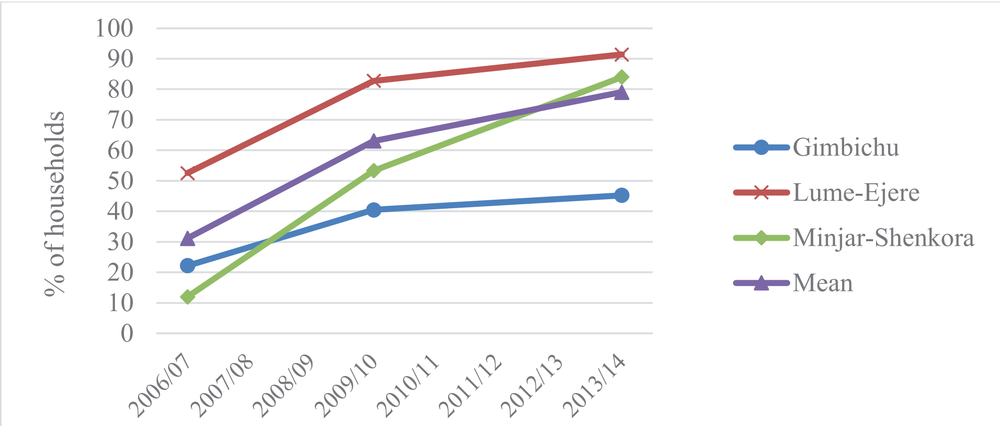

Figure 4.1 Adoption of improved chickpea by season and district

4.4.2 Determinants of Adoption

In this section we address the second question: *What were the main determinants of improved chickpea adoption?* Agricultural technologies can be defined as discrete inputs – either goods or methods – with the purpose of controlling and managing animal or vegetative growth (Parvan, 2011). Adoption decisions are influenced by many factors (Anderson & Feder, 2007). These factors can be broadly divided into characteristics of the technology, the intended users and the context within which adoption takes place (Biagini et al., 2014). We consider each of these factors in turn.

Technology characteristics

The promotion of Kabuli varieties began in 2004. Kabuli types are clearly distinguishable from the Desi type due to their different grain size and colour, which may have had a positive effect on uptake by facilitating trialability, observability and learning (Rogers, 1962). These characteristics determine the ease of learning about a new technology and its returns in settings where a technology is newly introduced (Foster & Rosenzweig, 2010). Access to improved seeds is another pre-condition for adoption (Asfaw et al., 2012). Improved varieties that had been multiplied by contract farmers were introduced via revolving seed funds, whereby a farmer pays in-kind with seed after harvest, and through seed grower associations (Monyo & Varshney, 2016). As chickpea is a self-pollinating crop the improved varieties could spread from farmer-to-farmer (Gwata, 2010).

We compared local and improved chickpea yields, returns and sales data for growers and sellers (Table 4.3). Improved chickpea yielded >20% more grain than local varieties with net returns from 50% greater to more than double. The larger land and initial labour allocations as well as input and hired labour costs of improved chickpea were easily compensated for by higher prices and productivity. Larger yields could be related to the higher labour and input use but also to the enhanced yield potential and disease resistance of the improved varieties (Dadi et al., 2005; Keneni et al., 2011). The Kabuli varieties fetched considerably higher prices than Desi related to the growing demand in both domestic and export markets (Abera, 2010; Shiferaw & Teklewold, 2007). Though more farmers sold local Desi in the first round, this completely reversed with 46% of growers selling local Desi in 2013/14 compared with 83% selling improved chickpea. During the focus group discussions farmers indicated that the market demand for Desi was largely replaced by Kabuli. Improved varieties provided an important source of cash, contributing 35 to 45% of total crop sales income compared with 18 to 22% for local Desi.

Adoption generally implies the reallocation of resources from existing activities (Bevan et al., 1990). The decision which crops to plant is thus based, at least partly, on weighing the relative investments (capital, land and labour) against the relative expected returns (Table 4.4). Kabuli generated the third largest returns among crops, only outperformed by lentil and wheat (2013/14 season). Cultivation of improved Kabuli incurred more costs than the other legumes in the first two survey rounds, but was less costly than cereals. This is to be expected due to the smaller amounts of fertiliser applied to legumes.

Although the seed rate for chickpea is large compared with cereals (Kassie et al., 2009), farmers can save seed (Asfaw et al., 2010). The capacity of legumes to fix atmospheric nitrogen can decrease the need for chemical fertiliser use and reduce costs in subsequent cereal crops (Giller, 2001). The economic benefits of enhanced cereal production and reduced fertiliser costs are not taken into account in our analysis. Chickpea was highly marketable with around 80% of households selling improved Kabuli and Desi. Chickpea fetched better prices than most crops, with the exception of teff and lentil in the last two rounds. There were no pronounced differences in terms of family labour allocation.

Table 4.3 Production, costs and returns of improved and local chickpeas

	2006/07			2009/10			2013/14		
	Local	Improved	t-test	Local	Improved	t-test	Local	Improved	t-test
Productivity (kg/ha)	1,917	2,315	***	1,998	2,377	***	1,933	2,472	***
Return to land (USD/ha)	2,517	3,785	***	1,704	3,679	***	1,165	2,016	***
Cultivated area (ha)	0.42	0.55	***	0.32	0.52	***	0.33	0.54	***
Family labour (days/ha)	75.5	85.0	**	82.8	73.5	*	75.6	74.4	
Crop cost (USD/ha)	277	529	***	234	424	***	234	338	***
Sold crop (yes=1)	0.87	0.80	**	0.67	0.86	***	0.46	0.83	***
Producers (Obs.)	320	197		290	388		156	479	
Sales price (USD)	1.45	1.90	***	0.97	1.72	***	0.76	0.95	***
Production sold (%)	58.3	71.1	***	51.3	60.4	***	35.6	56.4	***
Share of crop sales income (%)	22.2	35.3	***	18.0	44.5	***	22.1	41.1	***
Sellers (Obs.)	280	156		193	332		72	398	

Note: Significance levels * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4.4 Comparison of chickpea and other crop production characteristics (of growers / sellers)

		Improved Kabuli	Improved Desi	Local Desi	Teff	Wheat	Faba bean	Lentil
Productivity (kg/ha)	2006/07	2,342$_{a}$	2,167$_{a,b,d}$	1,917$_{b}$	1,568$_{c,e}$	2,506$_{a}$	1,650$_{c,d}$	1,438$_{e}$
	2009/10	2,455$_{a}$	1,757$_{b,d,f}$	1,998$_{b,c}$	1,549$_{d}$	2,740$_{e}$	1,866$_{c,f}$	1,498$_{d,g}$
	2013/14	2,477$_{a}$	2,414$_{a}$	1,933$_{b}$	1,738$_{c}$	2,786$_{d}$	1,988$_{b}$	1,503$_{e}$
Return to land (USD/ha)	2006/07	3,828$_{a}$	3,337$_{a,b}$	2,517$_{b}$	1,956$_{c}$	2,231$_{d}$	1,825$_{c}$	2,518$_{b,e}$
	2009/10	3,804$_{a}$	2,658$_{b}$	1,704$_{c,e}$	2,066$_{d}$	1,838$_{c}$	1,463$_{e}$	2,563$_{b}$
	2013/14	2,006$_{a}$	2,145$_{a,c,e}$	1,165$_{b}$	1,847$_{c}$	1,567$_{d}$	1,273$_{b}$	2,218$_{e}$
Family labour (days/ha)	2006/07	86$_{a}$	63$_{a,b,c}$	75$_{b,c}$	82$_{a,b}$	71$_{c}$	89$_{a}$	89$_{a}$
	2009/10	74$_{a}$	72$_{a,b}$	83$_{b,c}$	89$_{c,d}$	68$_{a}$	93$_{d}$	85$_{b,c,d,e}$
	2013/14	74$_{a}$	86$_{a}$	76$_{a}$	85$_{a}$	82$_{a}$	87$_{a}$	90$_{a}$
Crop cost (USD/ha)	2006/07	536$_{a}$	507$_{a,b,c}$	277$_{b}$	739$_{c}$	827$_{d}$	325$_{b,e}$	297$_{b,f}$
	2009/10	433$_{a}$	342$_{a,e,f}$	234$_{b}$	684$_{c}$	777$_{d}$	250$_{b,e,f}$	302$_{f}$
	2013/14	341$_{a}$	305$_{a,b}$	234$_{b}$	714$_{c}$	808$_{d}$	260$_{b,e}$	337$_{a}$
Sold crop (yes=1)	2006/07	0.79$_{a}$	0.75$_{a,b}$	0.87$_{b}$	0.80$_{a}$	0.83$_{a,b}$	0.45$_{c}$	0.84$_{a,b}$
	2009/10	0.85$_{a}$	0.86$_{a,d}$	0.67$_{b}$	0.66$_{b}$	0.63$_{b}$	0.47$_{c}$	0.79$_{d}$
	2013/14	0.83$_{a}$	0.85$_{a,c}$	0.46$_{b,d}$	0.72$_{c}$	0.53$_{b}$	0.44$_{d}$	0.73$_{c,e}$
Sales price (USD)	2006/07	1.91$_{a,f}$	1.68$_{a,b,c}$	1.45$_{b}$	1.76$_{c}$	1.23$_{d}$	1.34$_{e}$	1.99$_{f}$
	2009/10	1.72$_{a}$	1.68$_{a}$	0.97$_{b}$	1.88$_{c}$	0.98$_{b}$	0.94$_{b}$	1.88$_{c}$
	2013/14	0.95$_{a}$	0.97$_{a}$	0.76$_{b}$	1.50$_{c}$	0.87$_{d}$	0.77$_{b}$	1.69$_{e}$

Note: Values in the same row and subtable not sharing the same subscript are significantly different at $p< .05$ in the two-sided test of equality for column means. Cells with no subscript are not included in the test. Tests assume equal variances.

Household characteristics

We found systematic differences between adopters and non-adopters in demographics, welfare and livelihood indicators (Table 4.5). Adopters had larger households in the first two rounds and lower dependency rates in the last round. In addition, adopters more often hired labour in the first two rounds. Initial adopters were also slightly better educated, though overall education levels were poor.

Adopters were wealthier, with consistently greater incomes and lower poverty rates. Even though nominal incomes increased considerably, real incomes could not keep up with high inflation. In 2011, for example, Ethiopian food price inflation was 39%, three times the sub-Saharan African average of 13% (World Bank, 2015a). As a result, poverty rates of both adopters and non-adopters increased over the study period. Despite this loss in real per capita income, most households remained above the US$1.25 poverty threshold.

Adopters owned more assets, land and livestock, though differences became smaller over time as more households moved into the adopter category. Households owned more than 2 ha of land on average, which is relatively large considering that over 80% of farms in sub-Saharan Africa are now smaller than this (Lowder et al., 2014). In relation to livelihood diversification, non-adopters participated more in off-farm income generating activities and therefore had lower crop income shares in the last two rounds. Still, the effect of livelihood diversification was limited as crop income contributed 80 to 90% of total income.

Rogers (1962) indicated that technologies need to be compatible with the existing preferences and needs of adopters. Examples include taste preferences as well as specific processing and storage requirements (Lunduka et al., 2012). In terms of taste preferences, the focus group discussions revealed that farmers adjusted well to the newly introduced Kabuli varieties. Furthermore, Kabuli varieties were said to be easier to process due to their thinner seed coats which countered issues around poorer storability. Hence, it is unlikely that taste and other preferences hampered adoption and that they might have facilitated the adoption process.

Context

Adoption choices are conditioned by the context. Development actors need to take the specific context into account when designing interventions (Oumer et al., 2013). The functionality and structure of value chains as well as access to markets, influence input and output prices as well as transportation costs (Chamberlin & Jayne, 2013). The three selected districts are adjoining and differences in market access are relatively small (Table 4.6). The sites are close to Addis Ababa and other major markets, including Debre Zeit and Adama, and roads in the area are generally good. The FGDs revealed that market information, notably on prices, was available and known to farmers. Despite good overall market access, adopters were still located considerably closer to main markets.

The adequate and timely access to relevant advice and training can influence adoption (Anderson & Feder, 2007). Indeed, adopters had better access to extension, though extension access was almost universal and contacts were quite frequent across both adopters and non-adopters. This reflects Ethiopia's intensive public extension system (Gebremedhin et al., 2009; Krishnan & Patnam, 2013), which has an extension worker to farmer ratio of 1:476, compared to 1:1000 for Kenya, 1:1603 for Malawi and 1:2500 for Tanzania (Abate et al., 2015). The higher intensity of extension contacts of (early) adopters, suggests that extension had a positive effect on uptake. The high share of initial adopters in Lume-Ejere district also supports this, as Asfaw et al. (2012) noted that the district benefited from pre-extension demonstrations and improved seed distribution trials. While farmer-to-farmer technology transfer is generally important, the initial adoption was facilitated by a strong extension system allowing more innovative farmers to try the technology.

Agro-ecological characteristics such as soil quality, rainfall amount and distribution and the farming system can be important variables determining differences in adoption (Feder & Umali, 1993; Mason & Smale, 2013). Though variations in climate are relatively minor, the study area is located along a gradient: from higher elevations and rainfall in Gimbichu (2,411 meter, 675 mm) to lower elevation and precipitation in Minjar-Shenkora (1,896 meter, 565 mm). Initial adoption rates were highest in the central district of Lume-Ejere (50%). Minjar-Shenkora caught up with Lume-Ejere, while the high-elevation high-rainfall area of Gimbichu had the lowest adoption rates (45%) and farmers continued the cultivation of local Desi varieties (71%) and lentil (74%).

The data and FGDs reveal that the agro-climatic conditions in Gimbichu were less favourable for chickpea cultivation, particularly higher rainfall in combination with vertisols which are prone to waterlogging. Chickpea is highly sensitive to waterlogging and grown largely with residual moisture (Agegnehu & Sinebo, 2012). Because improved Kabuli varieties take approximately two weeks longer to mature than local Desi varieties, their cultivation in Gimbichu required relatively labour-intensive practices to remove excess moisture. Due to their shorter duration this is not required for local Desi and lentil, which may explain weaker adoption of the new varieties in Gimbichu.

Tenure security (Melesse & Bulte, 2015) and access to credit (Foster & Rosenzweig, 2010) are also potential determinants of adoption. As we did not collect detailed data on this we rely on the FGDs to assess their influence on adoption. As in the rest of Ethiopia, land is state-owned with individuals given usufruct rights whereby land cannot be sold, permanently exchanged for other property or mortgaged and inheritance is possible only by the immediate family (Ali et al., 2011). Nonetheless, recent land certification provided incentives for farmers to invest in their land (Wakeyo & Gardebroek, 2013) and it is thus unlikely that the lack of property rights influenced the adoption of improved chickpea. Though chickpea is an annual crop and requires less long-term investments than perennials, its residual soil fertility benefits in terms of increased yield of a subsequent cereal crop are part of its appeal to farmers (Giller, 2001).

There is widespread availability of credit in Ethiopia, particularly for inputs (Dercon & Christiaensen, 2011; Krishnan & Patnam, 2013). Data collected in the first round indicated that over 80% of households had access to credit (Asfaw et al., 2012), suggesting it is unlikely that credit was a constraint for uptake.

Table 4.5 Comparison of adopter and non-adopter household characteristics

	2006/07			2009/10			2013/14		
	Non-adopter	Adopter	t-test	Non-adopter	Adopter	t-test	Non-adopter	Adopter	t-test
Demographics									
Household size (No.)	6.08	6.76	***	6.00	6.59	***	5.63	5.81	
Dependents (%)	42.9	45.4		39.0	40.9		39.9	34.9	**
Hired labour (yes=1)	0.57	0.78	***	0.59	0.70	***	0.57	0.63	
Male head (yes=1)	0.93	0.96		0.94	0.95		0.91	0.91	
Education head (years)	1.59	1.98	*	1.87	1.99		2.14	1.81	
Age head (years)	46.3	47.9		49.3	48.1		50.3	52.0	
Income and poverty									
Total net income (USD)	4,541	7,760	***	4,145	7,008	***	3,404	4,696	***
Income per capita (USD)	837	1,232	***	806	1,175	***	670	885	***
Poor household (< $1.25)	0.28	0.11	***	0.37	0.20	***	0.48	0.27	***
Poor household (< $2.00)	0.57	0.32	***	0.58	0.39	***	0.70	0.54	***
Assets and livelihood									
Value assets (USD)	363	477	**	325	376	*	493	722	***
Land owned (ha)	2.01	2.67	***	2.00	2.41	***	1.94	2.17	*
Livestock owned (TLU)	4.77	7.33	***	4.91	6.23	***	4.58	5.04	
Off-farm income (yes=1)	0.29	0.24		0.30	0.21	**	0.39	0.25	***
Crop share total income (%)	89.8	91.5		85.3	90.7	***	80.8	87.8	***
Observations	417	189		224	382		127	479	

Note: Significance levels * p<0.10, ** p<0.05, *** p<0.01

Table 4.6 Comparison of adopter and non-adopter context characteristics

	2006/07			2009/10			2013/14		
	Non-adopter	Adopter	t-test	Non-adopter	Adopter	t-test	Non-adopter	Adopter	t-test
Travel time to the main market (min)	210	167	***	218	184	**	248	183	**
Extension contact (yes=1)	0.87	0.94	**	0.94	0.97	**	0.94	0.98	**
Extension contacts (days/year)	5.0	6.9	***	11.5	13.6	**	16.7	17.0	
Average rainfall past 5 seasons (mm)	595	605	**	636	614	***	632	590	***
St. dev. rainfall past 5 seasons (mm)	95.6	102.3	***	54.9	59.6	***	70.9	83.9	***
Elevation (m above sea level)	2,073	2,136	***	2,134	2,069	***	2,269	2,046	***
Black soil (yes=1	0.96	0.98		0.95	0.98	*	0.97	0.97	
Sandy soil (yes=1)	0.81	0.71	***	0.83	0.75	**	0.81	0.77	
Mixed soil (yes=1)	0.25	0.23		0.27	0.23		0.23	0.25	
Observations	417	189		224	382		127	479	

4.4.3 Returns to improved chickpea

In this section we address the question: *Are economic returns to improved chickpea good predictors of adoption?* Profits or net returns account for both changes in revenues from increased outputs or prices as well as changes in expenses from input adjustment (de Janvry et al., 2011). Labour and capital investments associated with adoption thus need to be considered (Jack, 2011). Using fixed effects (FE) estimation we assessed the effect of improved chickpea adoption on yields and chickpea returns (Tables 4.7 and 4.8).

Table 4.7 Fixed Effects (FE) estimation. Dep. variable: Ln chickpea yield (kg/ha)

VARIABLES	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Improved chickpea (yes=1)	0.1126				
	(0.106)				
Ln improved chickpea seed (kg)		0.0143			
		(0.020)			
Improved chickpea (% chickpea area)			0.0010		
			(0.001)		
Kabuli (yes=1)				0.0808	
				(0.098)	
Improved Desi (yes=1)				0.1483	
				(0.158)	
Local Desi (yes=1)				-0.0268	
				(0.067)	
Arerti (yes=1)					0.1362
					(0.083)
Shasho (yes=1)					0.1046*
					(0.061)
Ejere (yes=1)					-0.0814
					(0.103)
Dubi (yes=1)					0.1780
					(0.196)
Habru (yes=1)					-0.1304
					(0.105)
Chefe (yes=1)					0.3309*
					(0.171)
Marye (yes=1)					0.2605
					(0.284)
Constant	3.9610	3.9159	3.8282	3.9127	3.4680
	(4.170)	(4.164)	(4.156)	(4.178)	(4.203)
Observations	1,419	1,419	1,419	1,419	1,419
Households	581	581	581	581	581
Rho	0.512	0.510	0.510	0.512	0.518
R-squared overall	0.125	0.125	0.126	0.124	0.122

Note: Columns present fixed effects regressions for various indicators of improved chickpea adoption. Regressions include time-varying explanatory variables indicated in the Appendix, household fixed effects, year dummies and village time interactions. Fully robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01).

Table 4.8 Fixed Effects (FE) estimation. Dep. variable: Ln gross chickpea return (USD/ha)

VARIABLES	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
Improved chickpea (yes=1)	0.3865***				
	(0.109)				
Ln improved chickpea seed (kg)		0.0698***			
		(0.020)			
Improved chickpea (% chickpea area)			0.0047***		
			(0.001)		
Kabuli (yes=1)				0.2870***	
				(0.101)	
Improved Desi (yes=1)				0.3197**	
				(0.161)	
Local Desi (yes=1)				-0.1510**	
				(0.067)	
Arerti (yes=1)					0.2934***
					(0.085)
Shasho (yes=1)					0.2920***
					(0.064)
Ejere (yes=1)					0.0459
					(0.106)
Dubi (yes=1)					0.3873*
					(0.198)
Habru (yes=1)					-0.0192
					(0.103)
Chefe (yes=1)					0.5778***
					(0.180)
Marye (yes=1)					0.3262
					(0.342)
Constant	8.3921**	8.2628**	7.8409*	8.5421**	7.6196*
	(4.184)	(4.188)	(4.160)	(4.187)	(4.221)
Observations	1,419	1,419	1,419	1,419	1,419
Households	581	581	581	581	581
Rho	0.536	0.530	0.527	0.536	0.533
R-squared overall	0.138	0.141	0.151	0.137	0.139

Note: Columns present fixed effects regressions for various indicators of improved chickpea adoption. Regressions include time-varying explanatory variables indicated in the Appendix, household fixed effects, year dummies and village time interactions. Fully robust standard errors in parentheses (* $p<0.10$, ** $p<0.05$, *** $p<0.01$).

Despite promising on-station results we observed no significant increase in yield due to the adoption of improved varieties. This might be related to differences between chickpea varieties, because Chefe and Shasho did have between 10 and 33% higher yields (albeit only significant at $P<0.1$). FGDs suggested that disease resistance was an important incentive for adoption, but this is difficult to capture as benefits may only be apparent in seasons where pest and disease pressure is high.

There were consistent strong significant positive effects of improved chickpea adoption on chickpea returns, with 38% higher returns to improved chickpea. Moreover, using the same dataset we found that improved chickpea adoption significantly increased household income while reducing household poverty (Verkaart et al., 2017a). Disaggregating the analysis by chickpea type, it becomes clear that the results are related to both Kabuli and Desi adoption. Further disaggregation by variety shows that returns to Chefe, Dubi (Desi), Arerti and Shasho (from high to low) were significant, with 29 to 57% higher returns. This suggests that net returns are important predictors of adoption and emphasizes the importance of carefully measuring benefits and costs associated with new technology to explain adoption decisions.

4.5 Conclusions

We studied a case of successful adoption of improved chickpea varieties in Ethiopia using panel data. Though results for yields were unclear our findings suggest that improved chickpea resulted in higher returns, largely driven by superior Kabuli prices. Nevertheless, there are many alternative factors that can catalyse or impede uptake. Our analysis suggests that new innovations should offer distinct and visible benefits to facilitate adoption: be it high returns, disease tolerance or, as in our case, both. Other determinants that positively influenced adoption were the traditional importance of chickpea for livelihoods and within the farming system, as well as the good accessibility of markets and extension services. Overall, it seems that introducing an attractive and visibly distinct technology suitable for local households in a conducive environment enabled adoption.

What is noteworthy in our case is the absence of negative trade-offs: the technology was not overly complex or demanding in labour, inputs or cash investment. Rather than wondering whether all aspects always have to be right for adoption to take place, we reverse the question and ask: Why promote a technology when it increases risks or entails costs without sufficient reward? When it cannot be adopted due to various constraints and market imperfections? When it is too complex for the target group to understand? When households do not have sufficient land or are diversifying away from agriculture? When it does not fit taste preferences or when the agro-climatic conditions are not conducive for its cultivation? Indeed, success in technology adoption may not be about getting everything right, but about getting some important things right and avoiding many separate causes of failure.

Adopting a new technology will always be based on the expected benefits. As this involves risks, learning and investments, these benefits need to be substantial, particularly in the case of resource-poor smallholders. In the end, only innovations that substantially outperform locally available technologies and feature limited downside risks are likely to be adopted on a large scale. Though our results suggest that returns are good predictors of adoption, those returns are influenced by many external factors beyond the control of technology transfer interventions.

A good understanding of the local context and the likely attractiveness of a technology for a diversity of households in a specific location can provide information about potential benefits and pitfalls to avoid. This emphasizes the importance of careful site selection and targeting when disseminating innovations to ensure successful uptake. Robust evidence on what works, where and why, can be vastly instrumental in effectively assisting poor farmers. We suggest that agricultural research for development efforts need to more carefully consider the realities of smallholders if we are to design and deploy more successful interventions.

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Appendix

Table 4.A explanatory variable descriptives

	2006/07		2009/10		2013/14	
VARIABLES	mean	sd	mean	sd	mean	sd
Chickpea yield (kg/ha)	2,040	1,100	2,192	1,132	2,374	1,080
Gross chickpea return (USD/ha)	3,276	1,807	3,261	1,961	2,193	1,053
Improved variety (1=yes, 0=no)	0.312	0.464	0.630	0.483	0.790	0.407
Improved chickpea seed (kg)	34.23	79.27	60.70	80.05	89.60	101.8
Improved chickpea (% chickpea area)	22.63	37.08	51.10	43.43	72.74	40.58
Kabuli (yes=1)	0.305	0.461	0.569	0.496	0.734	0.442
Improved Desi (yes=1)	0.020	0.139	0.073	0.260	0.056	0.230
Local Desi (yes=1)	0.528	0.500	0.479	0.500	0.257	0.438
Arerti (yes=1)	0.078	0.268	0.193	0.395	0.503	0.500
Shasho (yes=1)	0.145	0.353	0.386	0.487	0.229	0.421
Ejere (yes=1)	0.127	0.333	0.002	0.041	0.000	0.000
Dubi (yes=1)	0.007	0.081	0.058	0.233	0.053	0.224
Habru (yes=1)	0.000	0.000	0.028	0.165	0.055	0.227
Chefe (yes=1)	0.010	0.099	0.008	0.091	0.003	0.057
Marye (yes=1)	0.002	0.041	0.003	0.057	0.003	0.057
Male head (1=yes)	0.936	0.246	0.942	0.233	0.914	0.280
Household size (No.)	6.295	2.250	6.368	2.358	5.772	2.089
Dependents (%)	43.70	20.49	40.21	19.62	35.98	21.60
Off-farm income (1=yes)	0.276	0.447	0.246	0.431	0.282	0.450
Land owned (ha)	2.215	1.308	2.257	1.299	2.122	1.281
Average rainfall past 5 seasons (mm)	97.70	15.50	57.85	12.64	81.18	12.04
St. dev. rainfall past 5 seasons (mm)	598.0	47.65	622.4	52.93	599.2	50.91
Chickpea seed (USD/ha)	270.9	234.4	272.7	123.6	189.7	98.04
Chickpea fertilizer (USD/ha)	20.98	86.95	12.83	72.47	18.48	78.75
Chickpea own manure (kg/ha)	9.049	67.52	11.40	184.0	27.48	343.2
Chickpea chemicals (USD/ha)	21.43	77.98	27.78	43.13	54.13	78.79
Chickpea hired oxen (USD/ha)	0.277	5.510	1.226	14.00	0.278	6.248
Chickpea hired labour (USD/ha)	33.72	78.64	32.01	75.08	53.07	99.69
Chickpea family labour (days/ha)	75.14	44.03	76.57	69.06	74.47	47.13
Observations	606		606		606	

Note: Chickpea production covariates were transformed to natural logarithm (ln) for the fixed effects estimation.

Chapter 5
Welfare impacts of improved chickpea adoption: A pathway for rural development in Ethiopia?

5

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Abstract

We analyse the impact of improved chickpea adoption on welfare in Ethiopia using three rounds of panel data. First, we estimate the determinants of improved chickpea adoption using a double hurdle model. We apply a control function approach with correlated random effects to control for possible endogeneity resulting from access to improved seed and technology transfer activities. To instrument for these variables, we develop novel distance weighted measures of a household's neighbours' access to improved seed and technology transfer activities. Second, we estimate the impact of area under improved chickpea cultivation on household income and poverty. We apply a fixed effects instrumental variables approach where we use the predicted area under cultivation from the double hurdle model as an instrument for observed area under cultivation. We find that improved chickpea adoption significantly increases household income while also reducing household poverty. Finally, we disaggregate results by landholding to explore whether the impact of adoption has heterogeneous effects. Adoption favoured all but the largest landholders, for who the new technology did not have a significant impact on income. Overall, increasing access to improved chickpea appears a promising pathway for rural development in Ethiopia's chickpea growing regions.

5.1 Introduction

Ethiopia is among the poorest countries in the world, is highly drought-prone and has an agricultural sector that accounts for 85 percent of employment (Dercon et al., 2012; Spielman et al., 2010). Exacerbating the situation, Ethiopia's population of 92 million is expected to grow to 160 million by 2050 (Josephson et al., 2014). As a result, farm sizes have been rapidly declining, increasing the need for agricultural intensification (Headey et al., 2014). Accordingly, increasing the productivity of smallholders through improved technology has become a policy priority for development agencies as well as the Ethiopian government (Abebaw & Haile, 2013). It has been suggested that tropical legumes can contribute to poverty reduction by improving food security and incomes of smallholder farmers in Africa (Gwata, 2010). One particularly promising technology is high yielding, drought tolerant chickpea varieties which can be used for on-farm consumption as well as export.

In this paper, we analyse the impact of adopting improved chickpea varieties on household welfare in rural Ethiopia. To do so we employ three rounds of panel data (2006/07, 2009/10, 2013/14) with a control function approach and instrumental variable estimation to control for endogeneity of access to improved seed, technology transfer activities and adoption.[6] We seek to answer the following research questions: What has been the impact of improved chickpea adoption on household income? To what extent did adoption contribute to poverty reduction? And, did adoption affect households differently depending on initial wealth status?

To motivate our empirical analysis, we first develop a simple conceptual framework using a non-separable model of a farm household that is simultaneously involved in both production and consumption decisions. We then estimate the area under improved chickpea using a double hurdle model. We apply a control function approach with correlated random effects to control for possible endogeneity of access to improved seed and participation in chickpea technology transfer activities. We develop a novel distance weighted measure to instrument for these endogenous regressors. Finally, we estimate the impact of area under improved chickpea on household income and poverty. We apply a fixed effects instrumental variables model where we use the predicted values from the double hurdle model as an instrument for observed area under improved chickpea cultivation.

Our primary contribution is to provide rigorous evidence on the impact of agricultural technology adoption on household income and poverty reduction. This comes at a particularly relevant time, as the 68th United Nations General Assembly declared 2016 the International Year of Pulses. Improved chickpea adoption increased dramatically from 30 to almost 80 percent of the sampled households between the 2006/07 and 2013/14 seasons. We find that adoption has a positive and significant impact on household income. Furthermore, households that adopt improved chickpea are less likely to be poor than households that choose not to adopt. We also isolate the impact of improved chickpea adoption on income

[6] Access to improved seed includes households that bought (from the market), borrowed (from a revolving seed fund) or were given (by friend/family/neighbour) improved seed. Technology transfer activities include farm trials or demonstrations, farmer field days, farmer field schools and seminars.

based on a household's initial land ownership. Improved chickpea adoption has a positive and significant impact on income for households with landholding in the three lower quartiles, but no significant effect on the income of the largest landholding households. The beneficial biotic and nutritional characteristics of legumes combined with our positive findings, implies that there is considerable potential for upscaling improved chickpea distribution networks for rural development in Ethiopia.

Our research contributes to a growing literature on the impact of technology adoption on poverty and income in sub-Saharan Africa, which has been thin and mixed (Cunguara & Darnhofer, 2011; Kassie et al., 2011). Much of the previous work has focused on hybrid maize, either in Kenya (Mathenge et al., 2014), Malawi (Bezu et al., 2014) or Zambia (Mason & Smale, 2013; Smale & Mason, 2014). Previous research on the impact of improved varieties of legumes does exist but, to date, has been hampered by data limitations. Research on chickpea in Ethiopia (Asfaw et al., 2012; Asfaw et al., 2010), groundnut in Malawi (Simtowe et al., 2012) and groundnut in Uganda (Kassie et al., 2011) all relied on cross-sectional data, which limited the ability of these studies to identify causal impacts. To our knowledge, no research exists that identifies the impact of improved legume adoption on farmer welfare in sub-Saharan Africa.

5.2 Background: Chickpea production in Ethiopia

Chickpea is an important crop in Ethiopia. The country is the seventh largest producer in the world and accounts for over 90 percent of sub-Saharan Africa's chickpea production (Kassie et al., 2009; Pachico, 2014). In Ethiopia chickpea is grown in rotation with cereals (primarily teff and wheat) and does not directly compete for land and labour with these cereals. Kassie et al. (2009) suggested that improved chickpea varieties are a key pro-poor and environmentally friendly technology for agricultural development and economic growth in Ethiopia. First, the growing demand in both the domestic and export markets provides a source of cash for smallholder producers (Abera, 2010; Shiferaw & Teklewold, 2007). Second, chickpea are considered environmentally friendly due to their capacity to fix atmospheric nitrogen and reduce chemical fertiliser use and costs in subsequent cereal crops (Giller, 2001). Finally, chickpea and its residues are a source of protein and can reduce malnutrition (Malunga et al., 2014; Sarker et al., 2014) and/or increase livestock productivity (Macharia et al., 2012).

The ability of Ethiopia's chickpea sector to foster economic growth and development depends on the country's ability to improve productivity, enhance grain quality and consistently supply the required volumes of market-preferred products at competitive prices (Abera, 2010; Keneni et al., 2011). More than ten improved chickpea varieties have been released (Asfaw et al., 2012). But until 2004, insufficient seed production limited the availability of quality seeds and the adoption of improved varieties was low (Shiferaw et al., 2007). Various initiatives were started to accelerate the adoption of improved chickpea varieties in Ethiopia. The Ethiopian Institute of Agricultural Research (EIAR) cultivated partnerships with major actors along the value chain to support the adoption of improved varieties (Abate et al., 2011). Primary co-operatives received breeder seed and multiplied them using contract farmers to enable the dissemination of improved chickpea varieties (Shiferaw et al., 2007). Moreover, the Tropical Legumes II (TLII) development program has conducted various chickpea research and development activities, including the establishment of seed grower associations (Monyo & Varshney, 2016).[7] TLII focused on major chickpea producing areas in the Shewa region for the upscaling of suitable chickpea varieties and marketing strategies. Other developments that boosted the chickpea sector included the decision to include chickpea in the Ethiopian commodity exchange and formation of the multi-stakeholder EthioPEA alliance.

Access to improved seeds and chickpea technology transfer are important pre-conditions for adoption. Krishnan and Patnam (2013) suggested that technology transfer activities provided by extension agents in Ethiopia transmit information vital to farmers in the early stages of adoption. They also found, however, that learning from neighbours who have adopted is more important than extension for the further diffusion of technologies. On chickpea, Asfaw et al. (2012) found that relatively affluent farmers had better access to improved seed in our study area which suggests that richer farmers might have been targeted through the extension system. They further note that Lume-Ejere district (one of our study areas) is strategically located on a main interstate road and closest to the national research centre that developed improved chickpea varieties, which might have disproportionately benefited farmers in the district in the form of pre-extension demonstrations and improved seed distribution trials. Thus, access to improved variety seed and chickpea technology transfer activities in the area was neither universal nor random. We adopt an instrumental variables approach to address the non-random access to improved varieties.

5.3 Conceptual Framework

It is too simplistic to assume that promoting agricultural technologies will automatically boost productivity, improve livelihoods and alleviate poverty (Tittonell, 2007). The potential effect of technology transfer depends on whether farmers adopt and, if they do, whether they adopt the technologies in an ideal combination and for the prescribed length of time needed to produce results (Parvan, 2011). For innovations that are 'divisible' and can be adopted in a stepwise manner the adoption decision involves a choice regarding the intensity of adoption (Marra et al., 2003). Adoption decisions are generally assumed to be the outcome of optimizing expected profit, where returns are a function of land allocation, the production function of the technology and the costs of inputs and prices of outputs (Feder et al., 1985). Often cited factors used to explain adoption are farm size, risk, human capital, labour availability, credit constraints, land tenure and access to input and output markets (Feder et al., 1985; Foster & Rosenzweig, 2010; Sunding & Zilberman, 2001). Adoption choices are also conditioned on agro-ecological characteristics, such as soil quality, rainfall patterns and the farming system (Mason & Smale, 2013). Adoption of improved varieties also depends

[7] Tropical Legumes II was a Bill and Melinda Gates funded project to enhance grain legume productivity and production to increase poor farmers' income in drought-prone areas of sub-Saharan Africa and South Asia. It was led by ICRISAT in partnership with CIAT, IITA and NARS partners and has just been renewed for a third phase (Tropical Legumes III).

on the availability and accessibility of improved seeds and training in chickpea cultivation (Asfaw et al., 2012), which is a concern in our context.

Further complicating measurement of adoption and its impact on welfare is the likely non-separability of household production and consumption decisions. In Ethiopia, smallholder farmers operate in an institutional environment characterized by failures in the labour, input and credit markets (Asfaw et al., 2012; Gebremedhin et al., 2009; Teklewold et al., 2013). As a result, households are simultaneously involved in both production and consumption decisions and the assumption of separability between these decisions is unlikely to hold. Accordingly, we analyse improved chickpea adoption using a non-separable model of the farm household, in which family members organize their labour to maximize utility over consumption goods and leisure in an economic environment with market failures (de Janvry et al., 1991).

Households produce goods for consumption or sale and cash constraints are relaxed primarily through farm sales of surplus products and off-farm income (Smale & Mason, 2014). Household endowments of natural, human, financial, physical and social capital constitute the resource constraints based on which well-being is maximized (Asfaw et al., 2012). In addition to factors of production, our model of adoption includes household demographic characteristics. Let K represent the area of land planted with improved chickpea

$$K = f(X, L, T, Z, V) \tag{1}$$

where X is a household's ability to cultivate improved seed (which incorporates both access to improved seed and technology transfer), L is the household's labour endowment and T is household demographic characteristics. Additional determinants include agro-ecological characteristics (Z) and village level covariates (V).

It is important to estimate the impact of technology adoption on household income and poverty, because this gives a measure of the extent to which the technology actually affects household welfare (de Janvry et al., 2011). Here we consider household welfare in a utility framework such that

$$Y = f(K, L, T, V) \tag{2}$$

where Y is household welfare and other variables are as previously defined. We use the two stage approach given in equations (1) and (2) to guide our empirical estimation procedure.

While conceptually both household welfare and technology adoption are functions of labour endowment, household demographic characteristics and village level covariates, the specific variables included need not have the same effect in both functions. As an example, the amount of off-farm income a household earns is likely to decrease adoption of improved chickpea (as farming is relatively less important) while it is likely to increase household welfare. With respect to our primary variable of interest, we hypothesize that growing higher yielding improved varieties will increase household income. This positive impact on welfare may be direct, through selling surplus chickpeas, or indirect, by releasing land to produce other crops for sale. If farmers use improved varieties successfully over several seasons, we expect that incremental increases in income could be capitalized to raise households above the poverty threshold (Mathenge et al., 2014). Accordingly, we test for a positive and significant impact of adoption of improved chickpea on both household income and poverty status. However, in contexts where households hold large areas of land on which they grow a wide diversity of crops or have other income sources, the average impact of adopting the improved variety could be insignificant (Mason & Smale, 2013). Therefore, in subsequent analysis, we allow for chickpea adoption to have a heterogeneous effect on income depending on a household's initial level of land ownership.

5.4 Data and descriptive statistics

5.4.1 Data

Our data comes from major chickpea producing areas in the Shewa region. Shewa is northeast of Debre Zeit, which is 50 km southeast of Addis Ababa. From the regions that have a suitable agro-ecology for chickpea production, three districts (Minjar-Shenkora, Gimbichu and Lume-Ejere) were purposely selected based on the intensity of chickpea production. In each district, eight to ten villages were randomly selected and within these 150–300 households were randomly selected. A total of 700 farm households in three districts were surveyed using a standardized survey instrument. Accordingly, our results are not nationally representative and should be interpreted as an upper bound of the potential impacts of improved chickpea adoption in the whole of Ethiopia. For further details we refer to Asfaw et al. (2012), who describe the sampling for the first round of the panel dataset and provide a more detailed account of the sampling strategy. The districts are in the central highlands at an altitude ranging from 1,700-2,700 meters. Chickpea is grown during the post-rainy season on black soils using residual moisture. Debre Zeit Agricultural Research Centre (DZARC) is located in the area and is a source of information and improved crop varieties, including chickpea.

We analyse the impact of improved chickpea variety adoption on household welfare in Ethiopia using three rounds of panel data (2006/07, 2009/10 and 2013/14). During the three survey rounds 700, 661 and 631 households were surveyed respectively. Since households were randomly selected both chickpea and non-chickpea growers were interviewed. Our analysis utilizes a balanced sample of 606 households. Balancing the panel results in an attrition rate of 13 percent. To check for non-random attrition we compared characteristics using the first round of data collected and found no significant differences between attritors and non-attritors.[8]

To enable comparisons across time, we deflated nominal Ethiopian Birr values to real values using the national consumer price index with 2005 as a base. These constant 2005 Ethiopian Birr data were subsequently converted to US dollar (USD) Purchasing Power Parity (PPP) values using rates extrapolated from the 2011 International Comparison Program (World Bank, 2015b).[9] We consider both the international poverty line of 1.25 USD PPP and median

[8] Results are available from the authors upon request.

[9] See Deaton (2010) for a thorough discussion of the measurement of poverty and the role of PPP price indexes.

poverty line of 2.00 USD PPP per day per capita (both in constant 2005 prices), which represent the lower and upper bounds of poverty (Ravallion et al., 2009). We calculate household welfare as annual net income per capita in constant 2005 USD PPP. We explicitly account for input and hired labour costs for crop production and livestock rearing using detailed information in our data regarding farm production.

Adopters are defined as households who plant an improved chickpea variety. As our measure of adoption in the econometric models we use the area allocated to improved varieties as an indicator for the extent or scale of adoption. Misidentification of varietal types is a common problem in many studies of adoption. This has led to a much more rigorous approach, sometimes using DNA fingerprinting, as a way to verify that farmers are actually growing what they say they are growing. However, the improved varieties in this study are predominantly newly introduced Kabuli chickpea types (95% of improved varieties). Kabuli was not traditionally cultivated in Ethiopia and are easy to distinguish from traditional Desi varieties. Kabuli are larger and cream coloured while Desi are smaller and brown. Additionally, the two varieties have a different flower colour. We are therefore confident that improved seed is correctly identified.

5.4.2 Descriptive statistics

Adoption of improved chickpea increased dramatically from 30 to almost 80 percent of the total sample (Table 5.1). In line with adoption, seed and land allocated to improved chickpea increased. Chickpea growers allocated half a hectare to improved varieties and it contributed up to twenty percent of total household income.

Table 5.1 Descriptive statistics improved chickpea adoption

	2006/07		2009/10		2013/14	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Panel A: Balanced sample						
Chickpea (yes=1)	0.655	0.476	0.805	0.396	0.881	0.324
Improved variety (1=yes)	0.312	0.464	0.630	0.483	0.790	0.407
Improved chickpea area (ha)	0.172	0.390	0.327	0.414	0.425	0.427
Improved chickpea seed (kg)	34.23	79.27	60.70	80.05	89.60	101.8
Improved chickpea share cultivated area (%)	5.925	11.67	12.11	12.96	18.90	14.24
Improved chickpea share total income (%)	7.023	13.80	15.84	16.94	16.23	13.21
Observations	606		606		606	
Panel B: Chickpea growers						
Improved variety (1=yes)	0.476	0.500	0.783	0.413	0.897	0.304
Improved chickpea area (ha)	0.263	0.457	0.406	0.425	0.482	0.423
Improved chickpea seed (kg)	52.25	93.04	75.38	82.78	101.7	102.7
Improved chickpea share cultivated area (%)	9.044	13.41	15.03	12.82	21.45	13.24
Improved chickpea share total income (%)	10.72	15.85	19.68	16.77	18.42	12.56
Observations	397		488		534	

Note: Panel A displays means and standard deviations of improved chickpea adoption indicators, by year, for the balanced sample. Panel B displays means and standard deviations of improved chickpea adoption indicators, by year, for households that grow chickpeas.

Table 5.2 indicates that there are systematic differences between adopters and non-adopters. Adopter households had significantly larger families in the first two rounds.

Table 5.2 Socio-economic characteristics of adopters and non-adopters

	2006/07			2009/10			2013/14		
	Non-adopter	Adopter	t-test	Non-adopter	Adopter	t-test	Non-adopter	Adopter	t-test
Demographics									
Household size (no.)	6.08	6.76	***	6.00	6.59	***	5.63	5.81	
Dependents (%)	42.9	45.4		39.0	40.9		39.9	34.9	**
Male head (yes=1)	0.93	0.96		0.94	0.95		0.91	0.91	
Education head (years)	1.59	1.98	*	1.87	1.99		2.14	1.8	
Age head (years)	46.3	47.9		49.3	48.1		50.3	52.0	
Welfare									
Total net income (USD)	4,541	7,760	***	4,145	7,008	***	3,404	4,696	***
Income per capita (USD)	837	1,232	***	806	1,175	***	670	885	***
Land owned (ha)	2.01	2.67	***	2.00	2.41	***	1.94	2.16	*
Value assets (USD)	363	477	**	325	376	*	493	722	***
Poor household (< $1.25)	0.28	0.11	***	0.37	0.20	***	0.48	0.27	***
Poor household (< $2.00)	0.57	0.32	***	0.58	0.39	***	0.70	0.54	***
Observations	417	189		224	382		127	479	

Note: Significance levels * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Other demographic indicators, including the head of the household's gender, education and age, did not differ between the two groups, though first round adopters had better educated household heads. Adopters were considerably wealthier than non-adopters, with higher total and per capita incomes across all three rounds. Differences in income and land become less stark over time, suggesting that early adopters were notably wealthier. Finally, poverty rates were substantially lower among adopters across the three rounds.

In this study we are interested in the dynamics of poverty, in particular, how poverty status changes with the adoption of improved chickpea. Though nominal incomes increased considerably between 2006/07 and 2013/14, real incomes could not keep up with high inflation experienced in Ethiopia (Figure 5.1). In 2011, Ethiopian food inflation was 39 percent, three times the sub-Saharan African average of 13 percent (World Bank, 2015a). As a result, poverty increased from 22 to 31 percent over the study period.

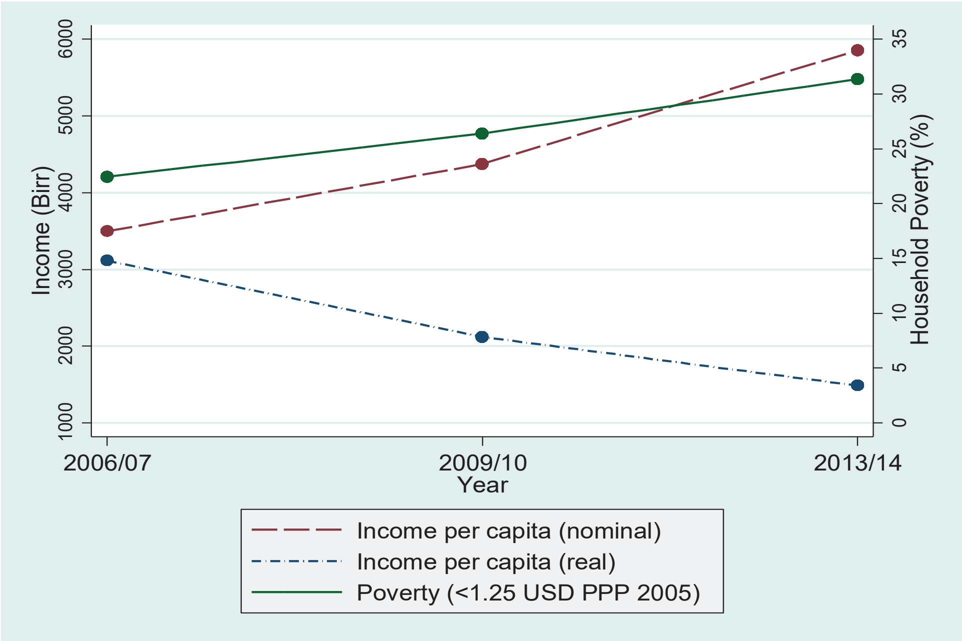

Figure 5.1 Poverty trends and income per capita in real and nominal Ethiopian birr

To better understand how household poverty changed over time we use data from 2006/07 and 2013/14 to draw the bivariate kernel density contours of real income per capita in constant 2005 USD PPP (see Figure 5.2). Circles indicate observed household data. To this, we have added dashed lines indicating the poverty line of 1.25 per day (constant 2005 USD PPP) and a solid 45° line. Households above the 45° line have more per capita income in 2013/14 than in 2006/07. Households below the 45° line have less per capita income in 2013/14 than in 2006/07. As expected, most of the mass lies below the 45° line with 57 percent of households having less real per capita income in 2013/14 than in 2006/07.

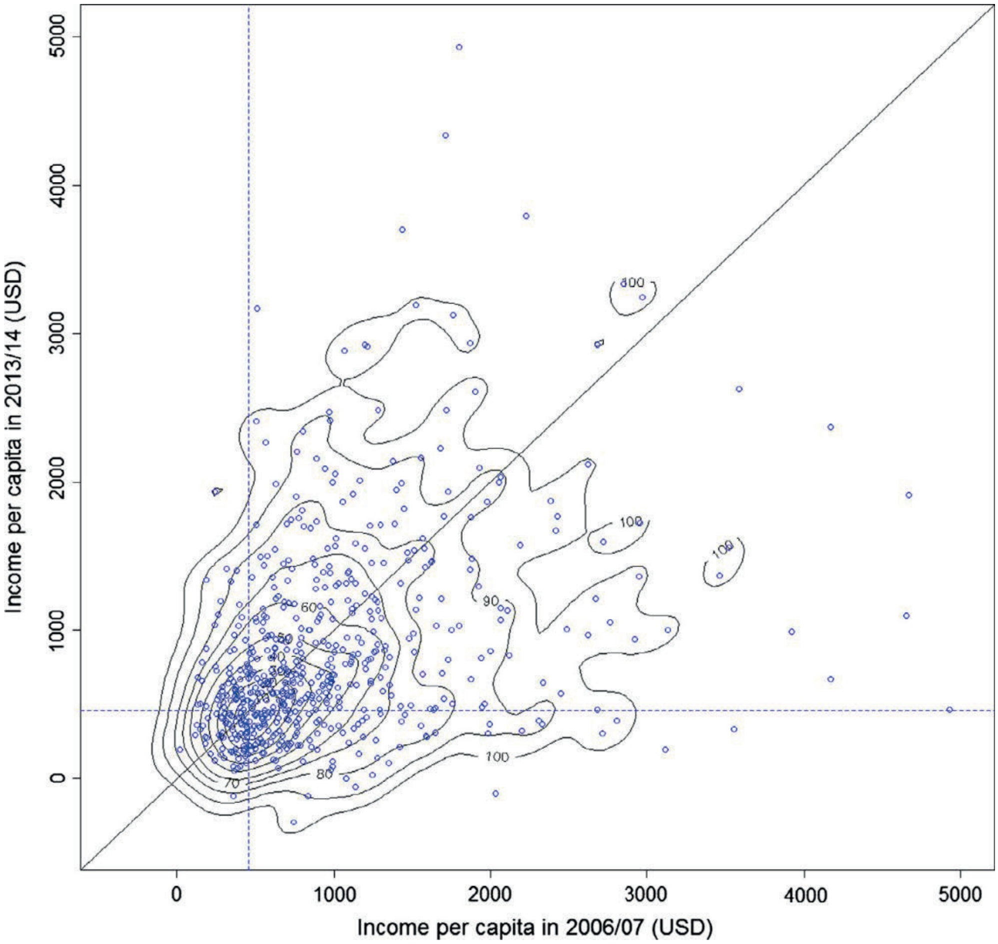

Figure 5.2 Bivariate density of mean real income per capita (constant 2005 USD PPP)

Despite this loss in real per capita income, most households remained above the \$1.25 poverty line. In fact, 59 percent of households were above the poverty line in 2006/07 and remained above the poverty line in 2013/14 (these households are in the northeast quadrant of Figure 5.2). A significant share of households, 19 percent, were above the poverty line in 2006/07 but by 2013/14 had fallen into poverty (southeast quadrant). Twelve percent of households started the study period in poverty and saw no change in their fortunes (southwest quadrant). Only 10 percent of households began 2006/07 below the poverty and were able to rise out of poverty by 2013/14 (northwest quadrant).

5.5 Empirical approach

5.5.1 Estimation of improved chickpea adoption

The objective of this study is to analyse the impact of improved chickpea adoption on household welfare. Starting from equation (1) in our conceptual model we specify the following

$$\mathrm{K}_{it} = \alpha + \beta_1 X_{it}^{TT} + \beta_2 X_{it}^{IS} + T_{it}\theta + Z_i\zeta + D_t + v + \epsilon_{it} \quad (3)$$

where K_{it} is the area planted with improved chickpea by household i in year t and X_{it}^{TT} and X_{it}^{IS} are our measures of access to technology transfer and improved chickpea seed, respectively. T_{it} is a vector of household characteristics and Z_i is a vector of time-invariant agro-ecological characteristics both of which influence the desirability of adopting improved chickpea. We also include year, D_t, and village, v, dummies to control for common shocks and unobserved regional characteristics that affect improved chickpea adoption. Finally, ϵ_{it} is a compound error term consisting of unobserved time-invariant factors, c_i, and unobserved time-variant shocks, υ_{it}, that affect improved chickpea adoption.

Table 5.3 provides descriptive statistics for the variables used in the model. Estimation of equation (3) is complicated by several econometric issues which make causal identification difficult. We address these in turn.

Unobserved heterogeneity

A first estimation issue is the presence of household heterogeneity that influences adoption but is otherwise unobserved. This unobserved heterogeneity creates selection bias as some households are more likely to adopt improved chickpea varieties than other households. The standard panel data method would be to include household fixed effects, which allows for arbitrary correlation between c_i and our household variables. However, the prevalence of households that grow no improved chickpea means that the data takes on properties of a non-linear corner solution (Ricker-Gilbert et al., 2011). To avoid the incidental variables problem that fixed effects introduces in non-linear models we adopt a correlated random effects framework, first pioneered by Mundlak (1978) and Chamberlain (1984). We assume that the unobserved heterogeneity can be replaced with its linear projection onto the time averages of all exogenous variables such that

$$c_i = \bar{T}_i\lambda_1 + u_i. \quad (4)$$

While not as weak of an assumption as used in fixed effects, since we specify the correlation between c_i and our household variables, correlated random effects does relax the strong assumption of no correlation required in a random effects model (Wooldridge, 2010).

Unobserved shocks

A second estimation issue is the possible presence of unobserved shocks captured in υ_{it} that might affect a household's access to and cultivation of improved chickpea. Given that the improved chickpea seed system is in its infancy, farmer's access to seed during the period of study was limited (Abate et al., 2011). Few farmers bought chickpea seeds and the percentage of farmers buying seed reduced over time, suggesting that seed replenishment rates went down. However, some farmers could access improved seed through buying (from the market), borrowing (from a revolving seed fund) or receiving as a gift (from family / neighbour). In addition, activities designed to improve farmer capacity were not universally available. Technology transfer activities include farm trials or demonstrations, farmer field days, farmer training centres, field schools and seminars, and participation in these activities increased over time. Seed dissemination and extension activities were often targeted to specific villages and farmers (Asfaw et al., 2012; Shiferaw et al., 2007). This means that access to technology transfer and improved seed are neither random nor static and thus likely correlated with unobserved time-varying factors.

Table 5.3 Descriptive statistics for variables used in the econometric analysis

	2006/07		2009/10		2013/14	
	Mean	s.d.	Mean	s.d.	Mean	s.d.
Distance to neighbours (km)	94.54	173.0	94.54	173.0	94.54	173.0
Technology transfer (1=yes)	0.013	0.114	0.127	0.333	0.150	0.358
Distance to technology transfer (km)	1.079	4.390	8.673	23.50	12.05	28.39
Lag weighted dist. tech. transfer (IV)	-	-	0.013	0.039	0.124	0.151
Access to improved seed (yes=1)	0.195	0.396	0.195	0.396	0.186	0.390
Distance to improved seed (km)	17.32	36.46	18.47	42.10	21.54	48.15
Lag weighted distance seed (IV)	-	-	0.191	0.221	0.201	0.184
Age head (years)	46.81	12.08	46.81	12.08	46.81	12.08
Education head (years)	1.713	2.647	1.713	2.647	1.713	2.647
Male head (1=yes)	0.936	0.246	0.942	0.233	0.914	0.280
Household size (no.)	6.295	2.250	6.368	2.358	5.772	2.089
Dependents (%)	43.70	20.49	40.21	19.62	35.98	21.60
Off-farm income (1=yes)	0.276	0.447	0.246	0.431	0.282	0.450
Land owned (ha)	2.215	1.308	2.257	1.299	2.122	1.281
Initial asset ownership (USD)	398.4	560.7	398.4	560.7	398.4	560.7
Walking distance to market (minutes)	196.5	84.50	196.5	84.50	196.5	84.50
Average rainfall past five seasons (mm)	598.0	47.65	622.4	52.93	599.2	50.91
St. dev. rainfall past five seasons (mm)	97.70	15.50	57.85	12.64	81.18	12.04
Black soil (yes=1)	0.969	0.174	0.969	0.174	0.969	0.174
Sandy soil (yes=1)	0.777	0.416	0.777	0.416	0.777	0.416
Mixed soil (yes=1)	0.246	0.431	0.246	0.431	0.246	0.431
Observations	606		606		606	

To control for unobserved shocks we adopt an instrumental variables approach. An appropriate instrument for this model must be correlated with a household's access to technology transfer and improved chickpea seed but uncorrelated with the amount of land under improved chickpea cultivation. We develop a spatial measure of access to improved seed and another for participation in technology transfer, each of which excludes a farmer's own access to seed and participation in technology transfer. The idea is that if neighbouring households have access to improved seed (participated in technology transfer), this will translate into a higher probability that the farmer in question will have access to improved seed (technology transfer). To ensure that causality does not run in reverse (farmer to neighbour instead of neighbour to farmer), we use the lagged value of each of our spatial measures as the instruments.

To construct our instruments we incorporate insights from recent research on the importance of social networks in technology adoption (Conley & Udry, 2010; Krishnan & Patnam, 2013; Magnan et al., 2015). While our data does not include information of social interactions or networks, it does include GPS coordinates for all households. We use this information to measure the distance between each surveyed household in a village. We also measure the distance between each household and every other surveyed household in the village that had access to improved chickpea seed (technology transfer). Using the inverse of these distances so that higher values correspond to nearer neighbours, we calculate two distance weighted ratios (one for access to seed and one for technology transfer) of neighbours with access to improved seed (technology transfer) to all households surveyed in the village. Thus,

$$W_{it} = \left(\sum \frac{x_{jt}}{d_{ij}}\right) / \left(\sum \frac{1}{d_{ij}}\right) \tag{5}$$

where W_{it} is the distance weighted ratio at time t of those with access to improved seed (technology transfer), x_{jt} is an indicator equal to one if neighbour j had access to improved seed (technology transfer) at time t and zero otherwise and d_{ij} is the distance between household i and household j. While distance is time-invariant, access to improved seed (technology transfer) varies from year to year so that our instrument is time-variant. By using distance to weight the binary variable indicating if a household had access to improved seed (technology transfer), we incorporate the idea that nearby households are more likely to be part of the same social network. Thus, a nearby household with access to improved seed (technology transfer) will have a larger impact on W_{it} than a distant household's access. By expressing W_{it} as a ratio, we control for a household's overall location within the village milieu so that living on the outskirts (or in the centre) of a village does not have a disproportionate effect on one's access to improved seed (technology transfer). Finally, by lagging the variables we resolve the potential simultaneity of access problem in which we cannot distinguish who (farmer or neighbour) first had access to improved seeds (technology transfer).[10]

To instrument for access to technology transfer and improved seed we use a control function (CF) approach developed by Smith and Blundell (1986). Our choice of the CF approach, instead of the standard two-stage least squares (2SLS) approach is driven by the prevalence of zeros in our adoption equation, giving it the properties of a non-linear corner solution. While in linear models CF leads to the 2SLS estimator, in non-linear models these two approaches will give different results (Imbens & Wooldridge, 2007; Lewbel, 2004). In these cases, the CF approach is more efficient than standard 2SLS.[11]

This involves first estimating the reduced form probit model to predict the access to technology transfer and improved seed (Wooldridge, 2010). We then calculate the generalized residuals and include them in the structural model of improved chickpea adoption specified in equation (3). In the reduced form equation we include all exogenous variables from the structural model, year and village dummies, as well as the means of time-varying

[10] We thank an anonymous reviewer for pointing out this potential confounder in the non-lagged version of our instruments, though, it still does not completely control for all potential unobservables. Having controlled for time-invariant household and village level effects and (in a robustness check) for time-variant village level effects, what remains are time-variant shocks at the sub-village level. These shocks would need to systematically only effect the ability to access seeds or technology transfer for a portion of residents in a village. If these events were then also correlated with a given household's decision to adopt chickpea in the following time period, we would have failed to fully identify the adoption decision. Our results should be interpreted with this in mind.

[11] Note that this efficiency comes at the cost of additional assumptions. These assumptions were originally laid out in Rivers and Vuong (1988) and relaxed in Wooldridge (2005) and are more restrictive than standard assumptions required in 2SLS estimation.

variables to control for unobserved heterogeneity.

Censored dependent variable

A final estimation issue in the adoption equation is how to deal with the censored dependent variable. As mentioned previously, between 21 and 68 percent of households are non-adopters in any given year. The prevalence of households that grow no improved chickpea means that our dependent variable is censored and our model is more appropriately expressed as a non-linear corner solution.

$$K_{it} = \max(0, \alpha + \beta_1 X_{it}^{TT} + \beta_2 X_{it}^{IS} + T_{it}\theta + Z_i\zeta + D_t + v + \epsilon_{it}) \quad (6)$$

This specification allows for the decision not to adopt improved chickpea to be optimal for some farming households. In this situation the tobit estimator may be used since zeros represent household choice and not missing data due to incidental truncation. However, the tobit estimator implies that the decision to adopt and the degree of adoption are determined by the same process. We follow Ricker-Gilbert et al. (2011) and Bezu et al. (2014) in using a double hurdle model to estimate adoption. The double hurdle model, as developed by Cragg (1971) relaxes the restrictions of the tobit estimator. The decision to adopt, the first hurdle, is estimated using a probit. Then the degree or intensity of adoption, the second hurdle, is estimated using a truncated normal regression model. In each hurdle we include all exogenous variables, our endogenous variables, the generalized residuals, the means of time-varying variables and year and village dummies. Since we include the generalized residuals from the reduced form equation we bootstrap the standard errors, since they are likely biased.

5.5.2 Estimating the impact of improved chickpea adoption

While an important metric, estimating chickpea adoption is not our primary focus. Rather, we are interested in understanding the welfare impacts for those who adopt improved chickpea. To do this, we specify equation (2) in our conceptual model as the following

$$Y_{it} = \alpha_i + \phi K_{it} + T_{it}\theta + D_t + \epsilon_{it} \quad (7)$$

where Y_{it} is our welfare measure variously defined as total net income, net income per capita, an indicator for household poverty status at 1.25 USD PPP and at 2.00 USD PPP. Other variables are as previously defined. As with our model of improved chickpea adoption, our model of household welfare suffers from two potential sources of endogeneity. The first potential source of endogeneity comes from unobserved heterogeneity. Time-invariant household characteristics which are unobserved may be correlated both with adoption and with our welfare measures. Here again we have the issue of selection bias, where some households, depending on skill, risk preferences, etc., are likely to adopt a new technology while also having higher welfare measures *ex ante*. Given that our specification of household welfare is linear, we no longer have the incidental variables problem and utilize fixed effects to control for unobservables.

The second potential source of endogeneity comes from unobserved shocks that jointly influence the decision to adopt improved chickpea as well as a household's welfare status.

Such shocks could be covariate (such as weather events) or idiosyncratic (such as a death in the family). We include mean rainfall over the last five years and its standard deviation to help control for covariate shocks related to weather.[12] To control for additional, primarily idiosyncratic, shocks we follow Bezu et al. (2014) in using the unconditional expected values of area planted with improved chickpea as an instrument for observed adoption. First, we estimate adoption using the double hurdle model as previously outlined. Second, we calculate the unconditional expected values of adoption using the predicted values from the double hurdle model. Finally, we estimate the welfare equation using fixed effects and instrumenting for our variable of interest (observed area of land under improved chickpea) with the expected values of adoption.[13] In general this approach is more efficient than standard 2SLS and it is also more efficient than the CF approach in linear models (Wooldridge, 2003).

The variables which are excluded from the outcome equation and provide us with the exogenous variation necessary for identification are: soil characteristics, distance to market, access to seed and access to technology transfer. While we do not expect that soil characteristics and distance to market will be directly correlated with income after controlling for improved chickpea planted, they also do not provide enough variation to identify the instrument for both years separately (on their own they could only identify a single value for each household, not a value for each household in each year). Therefore, we rely on access to seed and technology transfer, variables that also satisfy the exclusion restriction, to provide variation in our instrument over time.

5.6 Results

We first estimate equation (6) using the correlated random effects double hurdle model treating access to improved seed and technology transfer as exogenous. In this specification both terms are significant and positively correlated with the probability of planting improved chickpea. However, neither are significant in the second hurdle (see columns (1) and (2) in Table 5.4). Next we treat access to improved seed and technology transfer as endogenous and instrument for these terms using each of our distance weighted measures of access by including the generalized residuals from each of the first stage, reduced form regressions.[14] The coefficient for the generalized residual for access to improved seed is significant in the first hurdle (see column (3) in Table 5.4), suggesting that access to improved seed is endogenous to the decision to adopt improved chickpea. The coefficients for participation in technology transfer and its generalized residual are not significant in the first hurdle, but are significant in the second hurdle (see column (4) in Table 5.4), which indicates that participation in technology transfer may not be important in the decision to adopt but is important in the extent of adoption.

[12] Our rainfall data comes from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). See Funk et al. (2015) for detailed information on the data.

[13] We use a linear probability model to estimate the poverty regressions instead of a probit or logit as these non-linear models carry several costs as outlined by Dercon et al. (2009).

[14] See the Appendix for results from the first stage regressions of access to improved seed and technology transfer.

Table 5.4 Adoption decision: Cragg's double hurdle model using correlated random effects estimation

	Technology transfer and seed access exogenous		Technology transfer and seed access endogenous	
	(1) Probability of planting (Hurdle 1)	(2) Area planted (Hurdle 2)	(3) Probability of planting (Hurdle 1)	(4) Area planted (Hurdle 2)
Chickpea technology transfer access (yes=1)	6.370***	0.051	-0.362	0.436***
	(1.337)	(0.032)	(1.179)	(0.163)
Generalized residual access technology transfer	-	-	0.608	-0.233**
			(0.650)	(0.092)
Access to improved chickpea seed (yes=1)	0.663**	0.003	1.608	0.181
	(0.265)	(0.038)	(2.013)	(0.194)
Generalized residual access seed	-	-	3.026***	-0.074
			(1.013)	(0.111)
Age head (years)	-0.006	-0.002*	-0.020***	-0.001
	(0.006)	(0.001)	(0.007)	(0.002)
Education head (years)	0.002	0.014**	0.023	0.014**
	(0.028)	(0.007)	(0.029)	(0.007)
Male head (yes=1)	0.208	-0.053	0.507	-0.038
	(0.693)	(0.096)	(0.609)	(0.111)
Household size (No.)	-0.084	0.026***	-0.114*	0.043***
	(0.063)	(0.010)	(0.066)	(0.011)
Dependents (%)	0.000	-0.001	0.002	-0.001
	(0.005)	(0.001)	(0.005)	(0.001)
Off-farm income (yes=1)	-0.392**	0.015	-0.495***	0.002
	(0.190)	(0.039)	(0.174)	(0.036)
Ln initial asset ownership (USD)	0.117*	0.088***	0.151**	0.083***
	(0.069)	(0.016)	(0.074)	(0.016)
Ln land owned (ha)	0.247	0.263***	0.332	0.257***
	(0.306)	(0.055)	(0.280)	(0.054)
Ln distance to market (km)	-0.420	0.052	-0.243	0.053
	(0.368)	(0.070)	(0.395)	(0.070)
Average rainfall (mm)	0.032**	0.004	0.029**	0.002
	(0.013)	(0.003)	(0.013)	(0.003)
St. dev. of rainfall (mm)	0.057***	0.001	0.051***	-0.002
	(0.010)	(0.003)	(0.010)	(0.003)
Black soil (yes=1)	-0.137	0.020	-0.633*	0.059
	(0.353)	(0.073)	(0.377)	(0.074)
Sandy soil (yes=1)	-0.029	-0.000	0.095	-0.006
	(0.143)	(0.034)	(0.146)	(0.035)
Mixed soil (yes=1)	0.151	-0.025	0.261*	-0.025
	(0.125)	(0.035)	(0.138)	(0.033)
Constant	2.069	-1.657	5.765	-2.044**
	(4.979)	(1.032)	(5.552)	(0.987)
Sigma		0.281***		0.279***
		(0.012)		(0.012)
Observations	1,212		1,212	
Number of households	606		606	
Bootstrapping replications	1000		1000	

Note: The first double hurdle regression (column 1 and 2) treats technology transfer and access to seed as exogenous to the decision to adopt. The second double hurdle regression (column 3 and 4) includes first stage residuals to control for potential endogeneity of technology transfer and access to seed. Results from the first stage reduced form regression are presented in the Appendix (Table 5.A). Fully robust bootstrapped standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01). Regressions include the means of time-variant variables, year dummies and village dummies.

Examining the other variables in the double hurdle model, the extent of adoption, but not adoption, is strongly and positively correlated with landholding. This result indicates that while additional landholding may or may not influence adoption, households with more land allocate larger tracts to improved varieties. Wealthier households were both more likely to adopt and allocated more land to improved chickpea, which confirms our descriptive finding that adopters are wealthier and that richer households may have been targeted by extension. Off-farm income is negatively related to chickpea adoption, suggesting that having additional sources of income reduces a household's ability or interest in adopting new agricultural technologies. Age and education of the head of household do not influence the choice to adopt but older and less educated household heads allocate less land to improved varieties, possibly indicating risk-aversion and technology mistrust as suggested by Bezu et al. (2014).

The fixed effects models provide evidence on the relationship between improved chickpea adoption and our various welfare indicators (Table 5.5).

Table 5.5 Adoption impact: Fixed effects instrumental variable estimation

	(1) Ln income per capita	(2) Ln household income	(3) Poor (< \$1.25)	(4) Poor (< \$2.00)
Ln improved chickpea area (ha)	1.261**	1.226**	-0.274	-0.388*
	(0.551)	(0.605)	(0.203)	(0.207)
Male head (yes=1)	0.177	0.189	-0.196**	0.056
	(0.185)	(0.187)	(0.098)	(0.112)
Household size (No.)	-0.113**	0.058	0.064***	0.087***
	(0.045)	(0.051)	(0.012)	(0.013)
Dependents (%)	-0.004	-0.004	0.000	0.001
	(0.004)	(0.004)	(0.001)	(0.001)
Off-farm income (yes=1)	0.208***	0.211***	-0.069*	-0.067
	(0.068)	(0.069)	(0.038)	(0.042)
Ln land owned (ha)	-0.019	-0.079	-0.293***	-0.241***
	(0.285)	(0.328)	(0.066)	(0.070)
Average rainfall (mm)	0.001	0.004	0.003	0.005
	(0.008)	(0.009)	(0.003)	(0.003)
St. dev. rainfall (mm)	0.021*	0.024*	-0.006**	-0.006**
	(0.011)	(0.013)	(0.003)	(0.003)
Kleibergen-Paap Wald F-statistic	67.176**	67.176**	67.176**	67.176**
Observations	1,212	1,212	1,212	1,212
Number of households	606	606	606	606
Bootstrapping replications	1000	1000	1000	1000

Note: Columns present fixed effects instrumental variables regressions for four different measures of household welfare as the dependent variable. In all models Ln improved chickpea area is treated as endogenous and instrumented with the predicted improved chickpea area from the endogenous double hurdle model in column (2) of Table 5.4. Fully robust bootstrapped standard errors in parentheses (* $p<0.10$, ** $p<0.05$, *** $p<0.01$). In addition to household fixed effects, regressions include year dummies.

The model is robust to our specification of income, showing a positive impact on both income per capita (Column (1)) and household income (Column (2)). Controlling for all other factors, a 10 percent increase in the area planted with improved chickpea is associated with a 12.6 percent increase in income per capita and a 12.3 percent increase in total income. Considering the impact on poverty, the fixed effects linear probability model indicates that adopting improved chickpea varieties can reduce the probability of a household being below the \$2.00 poverty line but is unable to reduce the probability of a household being below the \$1.25 poverty line. A 10 percent increase in the area planted with improved chickpea reduces the probability of being below the median poverty line by 3.9 percent. Changes in other covariates have the expected signs where they are significant.[15] We conclude that adoption of improved chickpea increases household income and that adoption can increase income to such a degree that it can raise households above the median poverty line. But, this increase in income is insufficient to raise the poorest households out of poverty. To verify the validity of our results to changes in our specification we conducted robustness checks (Table 5.6).

Table 5.6 Robustness checks of adoption impact

	(1) Ln income Per capita	(2) Ln household income	(3) Poor (< \$1.25)	(4) Poor (< \$2.00)
(1) Primary results	1.261**	1.226**	-0.274	-0.388*
	(0.551)	(0.605)	(0.203)	(0.207)
(2) Tech. trans. and seed access exogenous	1.327**	1.328*	-0.293	-0.382*
	(0.632)	(0.703)	(0.206)	(0.201)
(3) 1 % trim	1.341**	1.297**	-0.335*	-0.420**
	(0.564)	(0.616)	(0.199)	(0.209)
(4) Village time interactions	1.305**	1.293**	-0.361*	-0.440**
	(0.568)	(0.620)	(0.215)	(0.211)
(5) Ln improved chickpea seed (kg)	0.073*	0.069*	-0.027	-0.038**
	(0.039)	(0.042)	(0.018)	(0.019)
(6) Two-stage Tobit	2.088***	2.077***	-0.603*	-0.456
	(0.742)	(0.799)	(0.333)	(0.338)
Observations	1,212	1,212	1,212	1,212
Number of households	606	606	606	606

Note: Columns present fixed effects instrumental variables regressions for four different measures of household welfare as the dependent variable. Row (1) reports, for purposes of comparison, the results found in Table 5.5. Row (2) reports results using the predicted improved chickpea area from the exogenous double hurdle model in column (1) of Table 5.4 as an instrument for observed values. Row (3) reports results from the balanced panel when we trim the top and bottom 1% of observations based on initial income per capita. Row (4) includes village specific time trends to control for village specific trends that may be correlated with chickpea adoption. Row (5) presents an alternative specification in which the extent of adoption is measured by the quantity of improved chickpea seeds planted. Row (6) reports results in which we replace the CF double hurdle with a more standard two-stage instrumented Tobit prior to our fixed effects regression. Fully robust bootstrapped standard errors in parentheses (* $p<0.10$, ** $p<0.05$, *** $p<0.01$). Regressions include explanatory variables from Table 5.5, household fixed effects and year dummies.

In row (1) we present, for purposes of comparison, our primary estimation results. In row (2) we present results using the predicted values from the double hurdle model where access to improved seed and technology transfer are treated as exogenous. In row (3) we present results using a trimmed data set, where the top and bottom one percent of households, based on income per capita for the 2006/07 season, are removed. In row (4) we present results similar to our primary results but include village time trends at all levels instead of just village indicators. In row (5) we replace our preferred measure of the extent of adoption (area

[15] Running the model with value of assets and tropical livestock units owned as dependent variables did not give significant results. We hypothesize that there was insufficient time for adoption to contribute to asset accumulation.

planted) with the amount of seed planted. In row (6) we replace the control function in our model of adoption with a two-stage instrumented tobit prior to our fixed effects regression. Across all these alternative specifications we find that improved chickpea adoption has a strong positive impact on household income as well as a consistently negative impact on the probability of being below the median poverty line. However, our initial finding that improved chickpea adoption has no effect on households below the \$1.25 poverty line turns out to lack robustness. In some specifications we find a significant impact of improved chickpea adoption in reducing poverty while in other specification we find no impact at all.

While our econometric results provide strong evidence that adoption of improved chickpea varieties increases income and reduces median level poverty, Dercon and Christiaensen (2011), point out that households may not be equally able to capitalize on new technology. The very poorest households may have a reduced capacity to cope with shocks, due to a lack of capital, knowledge or access to markets, which keeps them caught in a poverty trap. Conversely, the wealthiest households may no longer be as reliant on agriculture and therefore may be less impacted by a new agricultural technology. In order to explore these possible heterogeneous effects of adoption we divide our data into quartiles based on a household's initial land ownership. We re-specify equation (7) as

$$Y_{it} = \alpha_i + \sum \phi_q (Q_q K_{qit}) + T_{it}\theta + D_t\delta + \epsilon_{it} \tag{8}$$

where Q is an indicator for the land ownership quartile (indexed by $q = 1, \dots, 4$) to which household i belongs. By allowing ϕ_q to vary by landholding we can test if adoption has heterogeneous effects on changes in welfare across initial wealth status.[16] Results presented in Table 5.7 show that the impact of adoption on welfare is strongly significant and positive for households in the three lower quartiles. However, adoption did not have a significant effect on welfare for the largest landholding households.

Table 5.7 Fixed effects estimation: Adoption impact by initial land ownership

	(1) Ln income per capita	(2) Ln household income
Initial quartile 1 * Ln improved chickpea area	2.227***	2.424***
	(0.752)	(0.821)
Initial quartile 2 * Ln improved chickpea area	1.269*	1.335*
	(0.732)	(0.809)
Initial quartile 3 * Ln improved chickpea area	1.469**	1.315*
	(0.677)	(0.738)
Initial quartile 4 * Ln improved chickpea area	0.180	0.109
	(1.193)	(1.306)
Observations	1,212	1,212
Number of households	606	606

Note: Columns present fixed effects instrumental variables regression results similar to those presented in Columns (1) and (2) of Table 5.5 except that the instrumented variable is interacted with an indicator for the initial land quartile to which each household belongs. Fully robust bootstrapped standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01). Regressions include explanatory variables from Table 5.5, household fixed effects and year dummies.

[16] This method is similar to that used by Hurst et al. (2010) and Michler and Balagtas (2015) to test for heterogeneous effects across groups without splitting the random sample based on a non-random criteria.

5.7 Discussion

Our results show the dramatic increase in improved chickpea adoption has had a strong positive effect on household welfare. This confirms the findings by Asfaw et al. (2012) who found a similar positive effect of improved chickpea adoption using the first round of data collected. There are several potential channels through which improved chickpea can increase household income. While a full exploration of these channels is beyond the scope of the current paper, we do provide some descriptive evidence on this issue. Table 5.8 presents inputs used in chickpea production as well as yield and sales information by adoption type. For inputs, improved varieties require costlier seed, use slightly more fertiliser and require more chemicals. Given that adopters of improved varieties plant significantly more land to chickpea, the cultivation of improved varieties also requires more labour. Households meet this increased labour demand by hiring more workers while family labour remains constant.

Table 5.8 Costs and Benefits of Chickpea Production

	Full Sample		
	Non-adopter	Adopter	t-test
Costs			
Chickpea area (ha)	0.19	0.65	***
Chickpea seed (USD/ha)	183	261	***
Chickpea fertiliser (USD/ha)	11.4	19.2	**
Chickpea chemical (USD/ha)	19.3	41.7	***
Chickpea hired labour (USD/ha)	24.2	46.1	***
Chickpea family labour (days/ha)	78.3	74.3	
Benefits			
Chickpea yields (kg/ha)	1,875	2,338	***
Sold chickpeas (yes=1)	0.37	0.87	***
Share of chickpea production sold (%)	54.3	58.0	*
Chickpea sales (kg)	401	857	***
Chickpea sales price (USD/kg)	1.25	1.33	**
Net returns to chickpea sales (USD)	739	1,727	***
Chickpea sales as share of income (%)	21.6	38.6	***
Observations	369	1,050	

Note: Significance levels * p<0.10, ** p<0.05, *** p<0.01

The increase in input use associated with improved chickpea cultivation contributes to significantly higher yields. These increased yields allow households to sell a larger share of their production into the market. While improved varieties command only a small mark-up, the return to improved chickpea is significantly higher given the significantly larger volume of sales. All this leads to chickpea sales making up a larger share of total income for those who adopt improved varieties. Our findings provide evidence that the adoption of improved chickpea can contribute to household income and poverty reduction in rural Ethiopia.

While we find strong impacts on income and evidence that adoption of improved chickpea can reduce median level poverty, we find little evidence that adoption was able to lift the poorest households above the $1.25 poverty line. One explanation for this result comes from Abro et al. (2014) who found that the poorest households in Ethiopia are more prone to income shocks. A particularly strong shock during our study period was the double digit inflation in Ethiopia (World Bank, 2015a). Dercon and Christiaensen (2011) suggested that the poorest households have a reduced capacity to cope with such large shocks while Dercon et al. (2012) found evidence of a serious ‘growth handicap’ for poor households in Ethiopia, which contributes to poverty persistence by inducing permanently lower outcomes. This suggests that additional efforts, beyond adoption of improved chickpea, may be required to lift the poorest households out of poverty.

We also fail to find evidence that improved chickpea adoption had a significant impact on the income of the wealthiest households, in terms of landholding. We hypothesize that this is due to households with large landholding being more diversified in their income sources. Households in the top quartile based on initial landholding were more likely to adopt improved chickpea: 68% of these households adopted compared to 55% of households in the lower three quartiles (significantly different at the 99% level). These households also planted a significantly larger area to improved chickpea (again significant at the 99% level). However, large landholding households were no different than households in the lower three quartiles when we examine the share of land area allocated to improved chickpea. Moreover, improved chickpea made up a smaller share of income for large landholding households compared to households in the lower three quartiles (significant at the 99% level). We interpret this to mean that while large landowning households adopted improved chickpea, the extent to which they reallocated land to chickpea was not large enough to make a significant impact on their income. Further research is needed to identify the mechanisms that can explain the disparate effects of adoption.

It has been suggested that improved chickpea varieties present an environmentally friendly technology for poverty reduction in Ethiopia (Kassie et al., 2009). This is important as increasing agricultural productivity by sustainably intensifying output per unit of land is deemed essential in Ethiopia (Josephson et al., 2014). Smallholder farming in Ethiopia is often subject to environmental disturbances such as drought, untimely or uneven distribution of rainfall and incidences of pests and diseases (Teklewold et al., 2013). Improved chickpea varieties are disease-resistant and drought tolerant. Moreover, chickpeas fix atmospheric nitrogen in soils, allowing farmers to save on chemical fertiliser use in subsequent cereal crops (Giller, 2001). As indicated by Lee (2005), environmentally sustainable technologies need to simultaneously generate positive agronomic and economic benefits if they are to achieve wide adoption. Our analysis provides evidence of the positive effect of chickpea adoption on both income and poverty reduction. Given the economic importance of chickpea in Ethiopia and the beneficial biotic and nutritional characteristics of legumes, improved chickpea seem to be a promising technology for sustainable intensification in Ethiopia.

Understanding the effects of improved chickpea adoption on household welfare is an important step in developing policies for chickpea growing areas in Ethiopia. Average adoption rates in Ethiopia are estimated to be much lower than those observed in our study area, though country-wide adoption figures are not available. In order to assess the potential for further upscaling it would be helpful to analyse the processes that facilitated the dramatic increase in adoption in our study area. Policies that remove obstacles for the diffusion of improved chickpea varieties can be important for addressing smallholder welfare. For instance, seed replenishment rates are low and attention is therefore needed to ensure that there is a sufficient and consistent supply of affordable quality chickpea seed. It is unlikely that the private sector will take up this challenge because farmers can re-use seed for up to five seasons (Jones et al., 2006). Hence, support is needed to strengthen farmer based seed systems to ensure improve accessibility of improved chickpea varieties. Ultimately, our results suggest that improved chickpea varieties could very well be an attractive pathway for rural development in Ethiopia's chickpea growing regions.

5.8 Conclusions

This article answers the empirical question: what is the impact of improved chickpea adoption on household welfare in rural Ethiopia? We estimate chickpea adoption using a double hurdle model with correlated random effects and then use predicted chickpea area from the double hurdle model to instrument for adoption in the fixed effects welfare estimations. We find that improved chickpea adoption significantly increases household income while also reducing median level poverty. To explore the possibility of heterogeneous effects of adoption, we disaggregate results by initial landholding and find that adoption favoured all but the largest landholding households, who adopted but not to an extent where adoption significantly affected their large and diverse income streams. Because our data comes from a region suitable for chickpea production, our positive findings are an upper bound on the potential for sustainable intensification of chickpea production in Ethiopia. With this caveat, our results provide concrete evidence for policies targeting poverty reduction in rural Ethiopia.

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Appendix

Table 5.A Correlated random effects probit model of access to technology transfer and seed

	(1) Technology transfer access (yes=1)	(2) Buys improved chickpea seed (yes=1)
Lagged weighted distance to technology transfer	-1.488***	
	(0.542)	
Lagged weighted distance to seed		-0.891***
		(0.267)
Age head (years)	-0.015***	-0.009**
	(0.005)	(0.004)
Education head (years)	-0.006	0.016
	(0.019)	(0.018)
Male head (yes=1)	-1.092**	0.395
	(0.437)	(0.447)
Household size (No.)	-0.144***	-0.012
	(0.043)	(0.046)
Dependents (%)	0.007*	-0.002
	(0.004)	(0.004)
Off-farm income (yes=1)	-0.149	-0.090
	(0.152)	(0.134)
Ln initial asset ownership (USD PPP)	0.096*	0.016
	(0.057)	(0.052)
Ln land owned (ha)	0.451*	-0.043
	(0.237)	(0.188)
Ln market distance (minutes)	-0.015	0.228
	(0.294)	(0.238)
Average rainfall (mm)	0.013	0.006
	(0.010)	(0.011)
Standard deviation rainfall (mm)	0.006	0.005
	(0.010)	(0.009)
Black soil (yes=1)	-0.196	-0.336*
	(0.238)	(0.204)
Sandy soil (yes=1)	0.056	0.086
	(0.128)	(0.106)
Mixed soil (yes=1)	0.032	0.097
	(0.117)	(0.098)
Year 2013/14	0.390	-0.004
	(0.264)	(0.252)
Constant	-6.624	1.655
	(4.731)	(3.282)
Observations	1,212	1,212
Number of households	606	606

Note: Column (1) presents first stage regression results predicting access to technology transfer with *lagged weighted distance to technology transfer* as an instrument. Column (2) presents first stage regression results predicting access to improved seed with *lagged weighted distance to seed* as an instrument. Fully robust standard errors in parentheses (* p<0.10, ** p<0.05, *** p<0.01). Regressions include the means of time-variant variables, year dummies and village dummies.

Chapter 6
Money matters:
The role of income and yields in agricultural technology adoption

6

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Abstract

Despite the growing attention to technology adoption in the economics literature, knowledge gaps remain regarding why some valuable technologies are slow to be adopted. This paper contributes to our understanding of the agricultural technology adoption literature by showing that a focus on yield-increasing technologies may, in some contexts, be misguided. We study a technology in Ethiopia that appears to have no impact on yields, but that has nonetheless been widely adopted. Using three waves of panel data, we estimate a correlated random coefficient model and calculate the returns to improved chickpea in terms of yields, gross revenue and net income. We find that farmers' comparative advantage does not play a significant role in their adoption decisions and hypothesize that this is due to the overall high economic returns to adoption, despite the limited yield impacts of the technology. Our results suggest economic measures of returns may be more relevant than increases in yields in explaining technology adoption decisions.

6.1 Introduction

Technological change is one potential pathway that can help countries and the households within them transition out of poverty. Understanding how firms and households in poor countries make their decisions about what technologies to adopt is therefore a central question. Despite the growing attention to technology adoption in the economics literature, knowledge gaps remain regarding why some valuable technologies are slow to realize their full potential. This paper contributes to our understanding of the agricultural technology adoption literature by showing that the focus on yield-increasing technologies may be misguided.

To economists, agricultural technology adoption decisions are assumed to be the outcome of individuals' optimization of expected utility or profit, where returns are a function of land allocation, the production function of the technology, the costs of inputs and prices of outputs (Feder et al., 1985). Under these assumptions, an empirical puzzle persists around the fact that adoption rates of many proven technologies, such as fertiliser and improved variety seeds, remains low among smallholder farmers in developing countries. The adoption literature has tackled this question head on, trying to explain the low adoption rates of technologies with high average returns.

Proposed answers to the puzzle include imperfections in credit markets (Croppenstedt et al., 2003), property rights (Place & Swallow, 2000), learning externalities (Conley & Udry, 2010; Foster & Rosenzweig, 1995) and lack of commitment (Duflo et al., 2011). Another explanation, proposed by Suri (2011), centres on heterogeneity in hybrid maize yields. While average returns might be high, farmers may face heterogeneous returns driven by factors rarely controlled for in adoption studies. Using a correlated random coefficient model, Suri (2011) confirms this hypothesis for hybrid maize adoption in Kenya. Thus, the empirical puzzle had a simple explanation: farmers with high yields adopted the technology while farmers with low yields failed to adopt, or dis-adopted the technology. This explanation of the puzzle has gained strong traction in the adoption literature, as evidenced by some 155 papers citing her results as of October 2016.

The adoption literature, especially in the past several years, frequently focuses on yield-increasing technologies. Since we assume that technology adoption centres around returns, this implicitly assumes that any marketable surplus can either be stored or sold at a profitable price. If the product is instead hard to sell or store, this may explain why adoption of high-yielding varieties remains low. Burke and Falco (2015) show large price fluctuations in the maize market in East Africa, suggesting that some barriers exist that prevent farmers from storing their produce and selling at more advantageous prices later on in the season. Potential barriers include limited post-harvest storage capacity (Ricker-Gilbert & Jones, 2015) and liquidity constraints (Stephens & Barrett, 2011). In addition, Cochrane's treadmill suggests that farmers are running in place because technology induced increases in productivity will eventually lead to lower prices (Cochrane, 1958; Levins & Cochrane, 1996). In Ethiopia, findings by Josephson et al. (2014) suggest the existence of an alternative treadmill, where farmers increase input use in response to declining soil fertility without yield increases, thus eroding returns. Observing yield increases alone would not take these factors into account.

Perhaps the assumed equivalence between yields and economic returns has led the literature astray. Instead of focusing primarily on yield increases, which may result in unmarketable surpluses or general equilibrium effects, we focus on the economic returns to technology adoption. In this paper, we apply Suri's (2011) methodology and assess heterogeneity in returns in a different country and with a different crop. Specifically, we explore returns to the adoption of improved chickpea varieties among smallholder farmers in Ethiopia. Existing local varieties produce small, tan seeds. The newly introduced improved varieties produce large cream coloured seeds which are highly prized in Middle Eastern and South Asian markets. We find widespread adoption of this technology even though yield gains from improved varieties are minimal when controlling for input use. Rather, what drives adoption is the existence of a market for small surpluses that allows households to increase both gross revenue and net income.

While adoption of improved chickpea varieties in Ethiopia has been rapid, it is still far from universal or uniform across regions. We want to assess to what extent net returns to improved chickpea varieties explain variation in adoption. We answer this question by addressing two sub-questions: (a) What is the heterogeneity in returns to the adoption of improved chickpea? (b) To what extent does heterogeneity in net returns explain differences in adoption? We use a model in which the returns to adoption that drive adoption decisions are allowed to vary across individuals. The theoretical model implies an underlying production function with correlated random coefficients (CRC). To estimate this model we use three rounds of household panel data and implement an expanded version of Suri's (2011) CRC model. This is in turn a generalization of the correlated random effects (CRE) model first outlined by (Chamberlain, 1984), as well as a generalization of the now standard fixed effects approach to panel data estimation.

The CRC approach allows for households to have both an absolute advantage in farming (equivalent to a fixed effect) and a comparative advantage in adoption (a household effect that is correlated with the adoption decision). By controlling for both sources of heterogeneity we are able to control for heterogeneity on yields, gross revenue and net income. Our estimation results imply that there is little heterogeneity in returns to the adoption of improved chickpea varieties among observed smallholder farmers in Ethiopia. This null result suggests that returns are relatively homogeneous, not heterogeneous, across households. The strong market demand for the improved chickpea variety, and associated high returns to adoption, dominates the heterogeneity effect. This provides an explanation for the high adoption rates, despite insignificant findings for yields.

Once we consider the market demand of the output from the new technology, comparative advantage is not a significant determinant in the decision to adopt, at least in the case of improved chickpea in Ethiopia. In contrast to other improved varieties in developing-country agriculture, adoption of improved chickpea varieties in Ethiopia has been relatively high and our results appear to explain this phenomenon. Our results suggest that the divergent adoption rates across contexts, such as the high adoption rates of technologies that provide only minimal improvements in yields or low adoption rates of high-yielding technologies, may be explained by net returns. Earlier technology adoption work focused more explicitly on profits and economic returns; our results suggest that future research should reorient in this direction to consider both the physical and the economic returns as factors that influence the adoption of agricultural technologies.

6.2 Data and descriptive evidence

6.2.1 Sources of data

We analyse the decision to adopt improved varieties of chickpea in Ethiopia using three rounds of panel data (2007, 2010 and 2014) collected for the Tropical Legumes II (TLII) program.[17] The districts in this study were purposively selected for their suitable agro-ecology for chickpea production and represent major chickpea growing areas in the country (Asfaw et al., 2012). The districts are in the Shewa region, roughly 50km south east of the capital, Addis Ababa. The study area is located in the central highlands at an altitude ranging from 1,700-2,700 meters and chickpea is grown during the post-rainy season on black soils using residual moisture. In each district, eight to ten villages were randomly selected and within these 150 - 300 households were randomly selected. Both chickpea and non-chickpea-growing farmers were interviewed. This resulted in 700, 661 and 631 households surveyed in each round. We limit our analysis to households interviewed in all three rounds of the survey, providing a balanced sample of 600 households and attrition rate of 14 percent.[18]

Adopters are defined as households who plant an improved chickpea variety in the season surveyed. Misidentification of varietal types is a common problem in many adoption studies of new seed technology. However, the improved varieties in this study are predominantly newly introduced Kabuli chickpea types (95% of improved varieties). Kabuli are easy to distinguish from traditional Desi varieties as they are larger and cream coloured while Desi are smaller and brown. Additionally, the two varieties produce different coloured flowers. We are therefore confident that improved seed is correctly identified.

The data includes detailed input use information, including purchased inputs, hired labour costs and family labour as well as demographic information (see Table 6.1). To enable comparisons across time, we deflated nominal Ethiopian Birr values to real values using the national consumer price index with 2005 as base following Bezu et al. (2012) and Verkaart et al. (2017a). These constant 2005 data were subsequently converted from Ethiopian Birr to US dollar (USD) Purchasing Power Parity (PPP) values using rates extrapolated from the 2011 International Comparison Program (World Bank, 2015b).

[17] The TLII development program has conducted chickpea research and development activities, including breeding of new varieties and the establishment of seed grower associations for production and distribution.
[18] To check for non-random attrition we compare characteristics at baseline and found no significant differences. Results available from the authors.

Table 6.1 Descriptive statistics by year

	2006/07		2009/10		2013/14		Total	
Chickpea yield (kg/ha)	2,038	(1,099)	2,183	(1,128)	2,372	(1,083)	2,214	(1,111)
Gross return to land (USD/ha)	2,850	(1,088)	2,674	(1,210)	2,250	(766.6)	2,564	(1,057)
Net income per capita (USD)	1,027	(746.0)	1,021	(780.7)	841.4	(656.9)	954.9	(731.3)
Chickpea price (USD/kg)	1.566	(0.403)	1.481	(0.404)	0.932	(0.132)	1.310	(0.438)
Chickpea area (ha)	0.612	(0.519)	0.618	(0.446)	0.578	(0.397)	0.602	(0.453)
Chickpea seed (kg/ha)	168.9	(170.0)	187.3	(79.60)	207.9	(109.1)	189.9	(122.4)
Fertiliser (kg/ha)	13.25	(53.28)	9.558	(57.81)	19.08	(131.2)	14.18	(91.85)
Manure (kg/ha)	8.360	(66.20)	11.49	(184.7)	27.68	(344.5)	16.71	(240.0)
Chemical cost (USD/ha)	17.98	(40.08)	27.38	(43.08)	54.04	(79.00)	34.79	(60.58)
Family labour (days/ha)	75.26	(44.13)	76.75	(69.32)	74.59	(47.26)	75.52	(55.08)
Hired labour cost (USD/ha)	33.81	(78.89)	31.87	(75.34)	52.62	(99.72)	40.22	(86.71)
Land preparation (USD/ha)	0.279	(5.531)	1.236	(14.11)	0.280	(6.272)	0.608	(9.560)
Male head (1 = yes)	0.944	(0.230)	0.944	(0.230)	0.923	(0.267)	0.936	(0.245)
Household size (No.)	6.546	(2.202)	6.572	(2.332)	5.830	(2.039)	6.286	(2.216)
Dependents ratio (%)	102.2	(75.48)	86.84	(66.28)	73.75	(64.81)	87.61	(69.96)
Off-farm income (1 = yes)	0.273	(0.446)	0.247	(0.431)	0.282	(0.450)	0.267	(0.443)
Land owned (ha)	2.215	(1.302)	2.255	(1.295)	2.116	(1.266)	2.195	(1.288)
Avg. 5 years rain (mm)	598.0	(47.88)	622.4	(53.16)	599.3	(51.11)	606.6	(51.97)
Rainfall shock index	0.321	(0.425)	2.214	(0.591)	0.355	(0.289)	0.964	(0.993)
Observations	600		600		600		1,800	

Note: First three columns of table display means of data by year with standard deviations in parenthesis. The final column displays means and standard deviations for the pooled data. All monetary units are given in real terms.

The TLII data is geo-coded at the household level, which allows us to match households to rainfall data using satellite imagery from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data. CHIRPS is a thirty-year rainfall dataset that incorporates 0.05° resolution satellite imagery with in-situ station data to create a gridded rainfall time series (Funk et al., 2015). The data provide daily rainfall measurements from 1981 through to the present. We map households into the 0.05° grid cells and calculate the cumulative rainfall for the rainy season immediately preceding chickpea planting. We then calculate the trailing five-year average of seasonal rainfall. To measure deviations from the mean, we follow Ward and Shively (2015) and Michler et al. (2016), in measuring rainfall shocks as normalized deviations in a single season's rainfall from expected rainfall over the previous five years.

6.2.2 Descriptive statistics

Overall, adoption rates of improved chickpea increased substantially during the study period. In 2007, 31 percent of households were recorded as growing improved varieties of chickpea. By 2014 the adoption rate had increased to 80 percent of households. Table 6.2 displays the transition history of adoption for households in the data. Of the 600 households in our sample, 25 percent always cultivate improved varieties of chickpea. A further 55 percent adopted improved varieties and remain adopters over the study period. Only 12 percent of households never adopted improved varieties, while 8 percent of households dis-adopted.

Table 6.2 Transitions across local/improved varieties for the sample period

	Transition of adoption			Fraction of sample (%)
	2006/07	2009/10	2013/14	(N = 600)
Always adopter	Y	Y	Y	24.67
Early adopter	N	Y	Y	30.79
Late adopter	N	N	Y	19.87
Mixed adopter	Y	N	Y	3.97
Mixed dis-adopter	N	Y	N	6.29
Late dis-adopter	Y	Y	N	1.49
Early dis-adopter	Y	N	N	1.16
Never adopter	N	N	N	11.75

Note: The table shows all possible adoption histories for the three years in our panel. In the middle three columns, the letters represent adoption status, where 'Y' represents the adoption of improved chickpea varieties while 'N' represents non-adoption or dis-adoption.

Adoption rates were not uniform across space or time. Figure 6.1 shows heterogeneity in the rate of adoption from round to round across the three districts in our study area. Adoption rates in Lume-Ejere were already over 50 percent when the survey began and by the end of the survey over 90 of households had adopted improved varieties. Minjar-Shenkora saw the most dramatic growth in adoption, increasing from 12 percent of households in 2007 to 84 of household in 2014. Compared to these two districts, adoption rates remained fairly stagnant in Gimbichu, where the initial adoption rate was 22 percent but only increased to 45 percent by 2014. Table 6.3 displays the transition history of adoption by district.

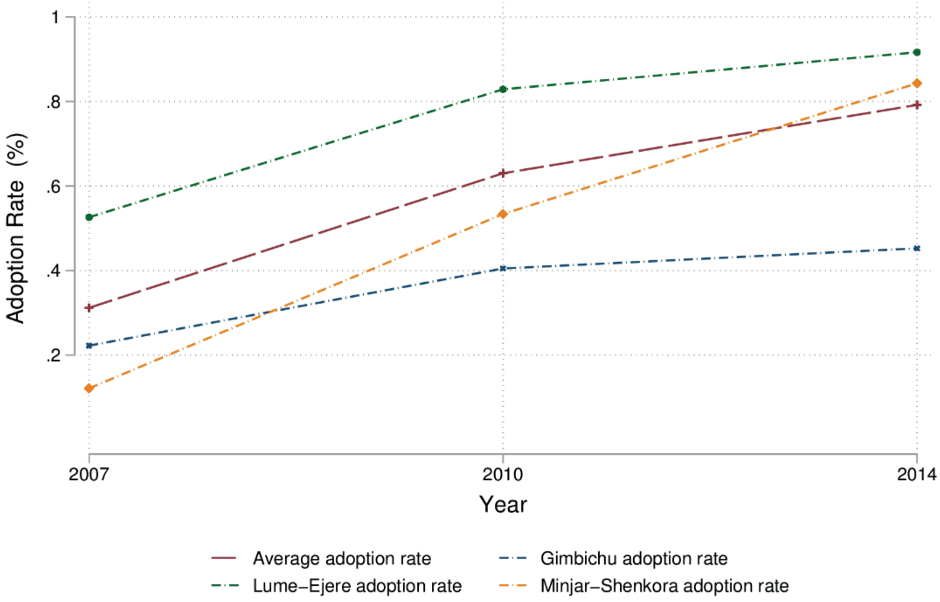

Figure 6.1 Average rate of adoption of improved varieties by district

Table 6.3 Transitions across local/improved varieties by district

	Gimbichu	Lume-Ejere	Minjar-Shenkora
Always adopter	13.49	45.67	7.14
Early adopter	11.11	31.50	41.07
Late adopter	16.67	10.24	32.59
Mixed adopter	3.97	4.33	3.57
Mixed dis-adopter	14.29	3.54	4.91
Late dis-adopter	1.59	2.36	0.45
Early dis-adopter	3.17	0.39	0.89
Never adopter	35.71	1.97	9.38
Observations	126	251	223

Note: The table shows the fraction of households from each district that follow a given adoption history.

One obvious explanation for heterogeneity in adoption is differences in agro-climatic zones across the districts. While all the districts are in the Shewa region, relatively close to each other and well suited for chickpea production, there are significant differences in growing conditions from district to district. Gimbichu receives, on average, 100mm more rainfall in a season than Minjar-Shenkora (674mm compared to 565mm). Gimbichu is also at a much higher elevation than either district (2,400m compared to just under 2,000m for the other two districts). Moreover, the district is characterized by vertisols which are prone to waterlogging. Chickpea is highly sensitive to waterlogging and grown largely with residual moisture (Agegnehu & Sinebo, 2012). Because improved Kabuli varieties take approximately two weeks longer to mature than local Desi varieties, their cultivation in Gimbichu required relatively labour-intensive practices to remove excess moisture. Due to their shorter duration this is not required for local Desi, which may explain the weaker adoption and dis-adoption of new varieties in Gimbichu.

Another potential source of heterogeneity is the ability of households to purchase plant protection chemicals.[19] Value chains for improved inputs, such as chemicals, remain poorly developed in Ethiopia (Shiferaw & Teklewold, 2007). Similar to the case of fertiliser and maize in Kenya as described by Suri (2011), the choice to purchase chemicals may be endogenous to the decision to adopt (i.e., correlated with the unobserved heterogeneity that drives the adoption decision). Table 6.4 presents summary statistics for production, costs and returns by adoption type. While the returns to adoption are clearly different across adoption type, most of the inputs show no clear pattern in intensity of use across varieties.[20] The one exception is chemical use, which is consistently higher for those households that cultivate improved varieties. In future work we aim to control for this potential source of endogeneity.

Much of the previous literature on agricultural technology adoption has focused on physical

[19] In our context we combine pesticide and herbicide into a single category, which we refer to from here on simply as chemical.

[20] For each cultivation pair we first test for normality of the data using the Shapiro-Wilk test. In every case we reject the null that the data is normally distributed. Because of this, we rely on the Mann-Whitney-Wilcoxon (MW) test instead of the standard t-test to determine if differences exist within crops across cultivation practices. Unlike the t-test, the MW test does not require the assumption of a normal distribution. In the context of summary statistics, we also prefer the MW test to the Kolmogorov-Smirnov (KS) test, since the MW test is a test of location while the KS test is a test for shape. Results using the KS test are equivalent to those obtained from the MW test.

returns, frequently yields. As a benchmark, we too consider returns to chickpea adoption in terms of yields. However, given that in many cases the adoption of a new agricultural technology is accompanied by an increase in input costs and markets for surplus yields may be missing, we incorporate two monetary measures of returns: gross revenue per hectare and net income per capita. Figures 6.2 – 6.4 show the marginal distributions for each variable by adoption status. For all three measures, returns and yields are higher for those who adopted.

6.3 Empirical approach

6.3.1 Theoretical framework

We begin by assuming that the decision to adopt is the outcome of optimizing expected profit, where returns are a function of land allocation, the production technology and the costs of inputs and prices of outputs (Feder et al., 1985). Focusing on the production technology, we assume a Cobb-Douglas production function. While agro-climatic differences across districts or differences in input use may explain some of the heterogeneity in adoption, this is not the same as the selection based on heterogeneous returns to technology as described in Suri (2011). Our goal is to control for these observable factors and determine if, conditional on observables, there is heterogeneity in the returns to adoption based on unobservable factors. The CRC model allows us to test this hypothesis.

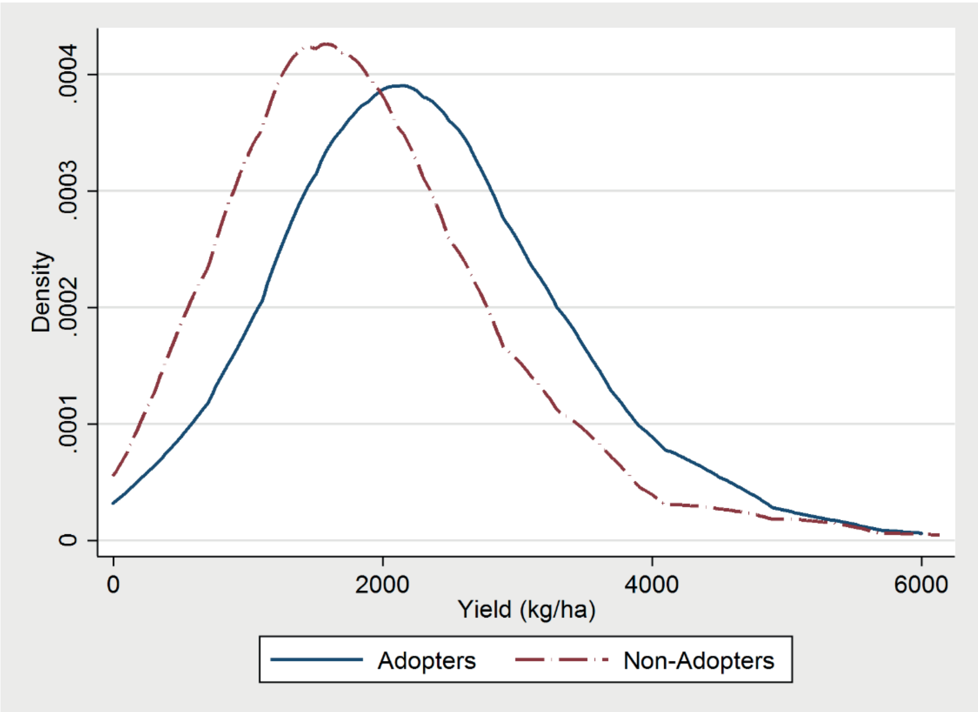

Figure 6.2 Marginal distribution of yields by adoption

Note: Figure displays the kernel density for yields for adopters of improved varieties and non-adopters.

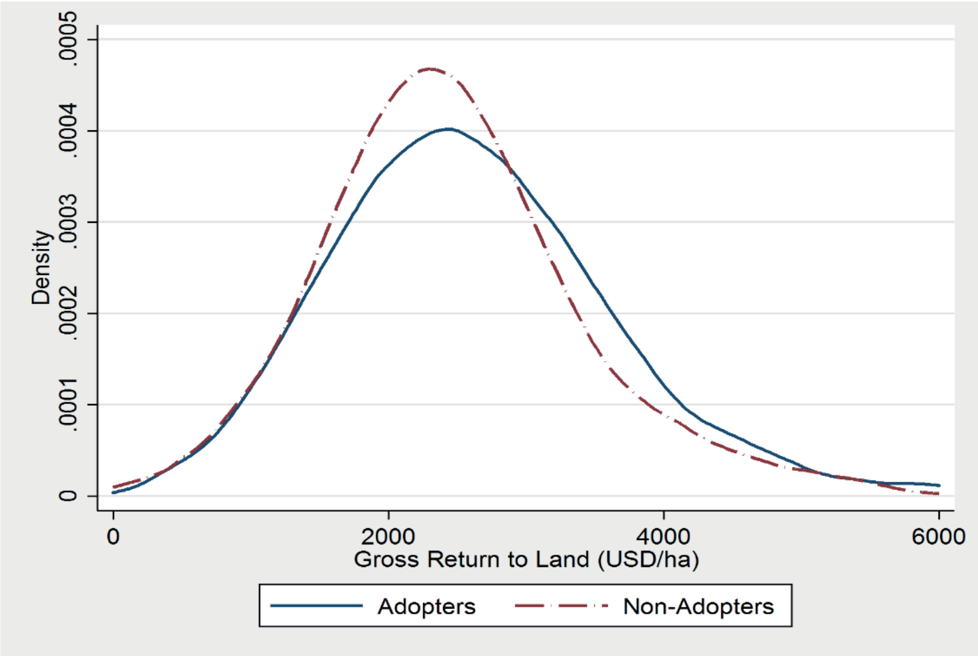

Figure 6.3 Marginal distribution of gross revenue to land by adoption

Note: Figure displays the kernel density for gross returns to land for adopters of improved varieties and non-adopters.

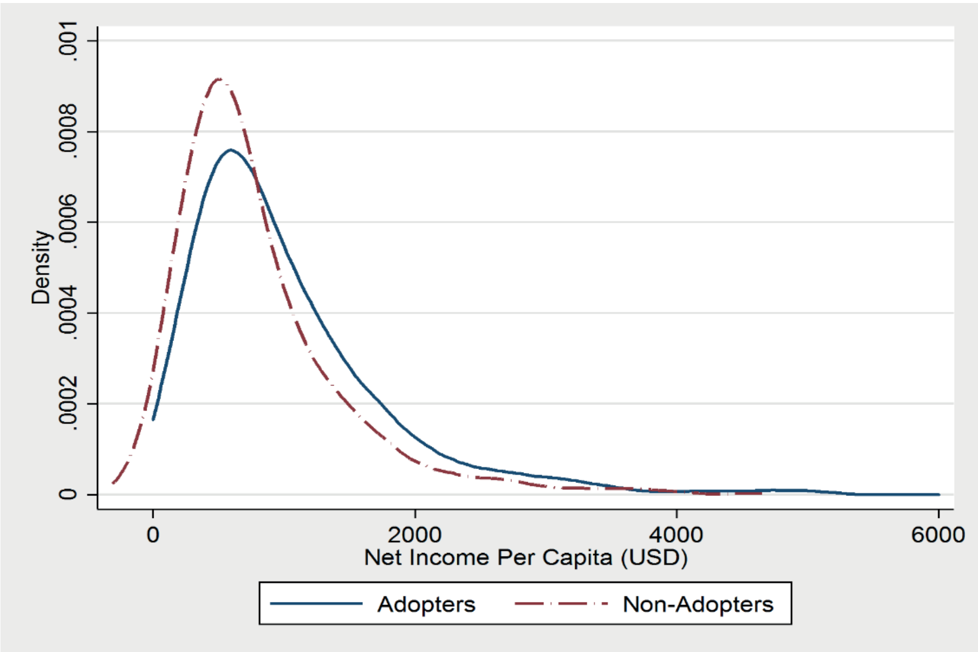

Figure 6.4 Marginal distribution of net income per capita by adoption

Note: Figure displays the kernel density for net income per capita (constant 2005 USD PPP per) for adopters of improved varieties and non-adopters.

The CRC model is a generalization of the household fixed effects model (Suri, 2006). Note that in a fixed effects model household unobservables have the same effect on yields regardless of the variety of chickpea grown. Intuitively, this assumes that the unobserved heterogeneity that makes the adoption decision endogenous is independent of a household's ability to cultivate the improved varieties. The CRC model relaxes this assumption and allows the unobserved effect to vary by chickpea variety.

In our estimation procedure we estimate the distribution of θ_i, which is a measure of a household's productivity in improved varieties relative to local varieties and φ, a measure of the importance of comparative advantage. The φ term describes the sorting of households into improved cultivation. For $\varphi > 0$, the sorting process leads to greater inequality in returns as households with relatively high values for θ_i select into the new technology and see increasing gains from their decision to adopt. Alternatively, for $\varphi < 0$, the sorting process leads to less inequality as adoption of improved varieties will still be optimal for households with relatively small values for θ_i. When $\varphi = 0$, a household's comparative advantage in cultivating improved varieties relative to local varieties is not important in the decision to adoption the improved varieties.

6.3.2 Identification of the yield function

Identification of the yield function requires two assumptions. The first is mean independence of the composite error, unobserved comparative advantage terms and the exogenous regressors. This assumption is not particularly strong. The second assumption is strict exogeneity of the idiosyncratic error term, which implies that transitory shocks do not affect the household's decision to adopt. We divide potential shocks into two categories - those that occur after the adoption decision and those that occur prior to the adoption decision. The timing of the household's decision is as follows. A household decides to plant or leave a given plot fallow. If it chooses to plant in that year they prepare the land. Following land preparation it chooses a seed technology based on forward-looking expectations regarding weather patterns, availability of inputs (including budget constraints) and prospects for the sale of outputs. Subsequently, the household plants and applies labour and complementary inputs throughout the growing season as weather shocks are realized. Finally, the household harvests and markets its production.

We are able to control for many of the shocks that occur after the adoption decision is made. We use deviations from average rainfall to control for rainfall shocks during the growing season. We also control for input use, as farmers will adjust their use of purchased inputs and the application of labour as seasonal weather shocks are realized. As Table 6.4 reveals, there are no clear patterns to input use based on the type of seed technology under use. In some years households who adopt improved varieties use more fertiliser, chemical and hired labour than households that cultivate local varieties. But in other years there are no significant differences in input use. We interpret this as households adjusting input use to the realization of transitory shocks after the adoption decision has been made. Given our inclusion of input values as controls, along with our inclusion of the rainfall term, we believe the possible presence of post-adoption transitory shocks is well controlled for.

Table 6.4 Production, costs and returns of improved and local chickpeas

	2007			2010			2014		
	Local	Improved	MW-test	Local	Improved	MW-test	Local	Improved	MW-test
Chickpea yield (kg/ha)	1,882	2,210	***	1,858	2,274	***	1,862	2,432	***
	(1,002)	(1,177)		(1,086)	(1,124)		(784.8)	(1,098)	
Gross return to land (USD/ha)	2,627	3,176	***	2,376	2,801	***	2,097	2,301	***
	(889.0)	(1,187)		(1,006)	(1,254)		(882.2)	(750.3)	
Net income per capita (USD)	828.3	1,206	***	811.3	1,093	***	672.1	873.2	***
	(599.6)	(844.4)		(681.3)	(805.7)		(659.3)	(653.8)	
Chickpea sales price (USD/kg)	1.420	1.728	***	0.992	1.586	***	0.788	0.941	***
	(0.335)	(0.412)		(0.224)	(0.353)		(0.177)	(0.124)	
Chickpea area (ha)	0.218	0.755	***	0.161	0.654	***	0.162	0.593	***
	(0.349)	(0.567)		(0.243)	(0.465)		(0.266)	(0.415)	
Chickpea seed (kg/ha)	135.3	206.0	***	186.2	187.6		202.2	208.5	
	(83.22)	(225.3)		(97.98)	(73.86)		(92.61)	(111.0)	
Fertiliser (kg/ha)	3.420	24.14	***	13.20	8.534		9.697	20.17	**
	(31.42)	(68.39)		(63.41)	(56.19)		(71.91)	(136.5)	
Chemical cost (USD/ha)	17.11	18.95		13.62	31.23	***	13.44	58.75	***
	(31.80)	(47.68)		(44.41)	(41.95)		(34.59)	(81.33)	
Family labour (days/ha)	73.07	77.69		91.02	72.75		73.31	74.74	
	(40.18)	(48.11)		(132.2)	(34.78)		(48.20)	(47.20)	
Hired labour cost (USD/ha)	16.98	52.45	***	23.55	34.21	***	53.20	52.55	
	(65.29)	(88.11)		(73.65)	(75.73)		(111.7)	(98.36)	
Observations	207	187		106	378		55	475	

Note: Columns in table display means of production data by year and by type of chickpea cultivated with standard deviations in parenthesis. All monetary units are given in real terms. Columns headed Local are output and inputs used in cultivation of local varieties of chickpea while columns headed Improved are output and inputs used in cultivation of improved varieties. The final column for each year presents the results of Mann-Whitney-Wilcoxon two-sample tests for differences in distribution. Results are similar if a Kolmogorov-Smirnov test is used. Significance of MW-tests are reported as * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

What remains are transitory shocks that occur prior to the adoption decision and affect both the decision to adopt and yields. We directly control for these potential shocks by including household demographic variables. As Suri (2011) points out, the most likely type of shock is sudden sickness or death in the family. We include variables to capture changes to the head of household, the household structure and the household's access to off-farm income on the assumption that a death would impact these terms. By including a rich set of control variables we have endeavoured to reduce the potential for transitory shocks to affect both the adoption decision and yields. However, including controls still leaves the possibility that some unobserved transitory shock remains. Such shocks, if they exist, most likely simultaneously reduce access to improved varieties and yields, meaning the returns to improved varieties may be biased upward. Our results should be interpreted in the light of this limitation.

6.3.3 Estimating the CRC model

A common difficulty in adoption studies is measuring or controlling for heterogeneity in the rate of returns to adoption. Heckman and Vytlacil (1998) and Wooldridge (2003) developed instrumental variable approaches to control for such correlated random coefficients. We use Suri's (2011) generalization of the CRE model pioneered by (Chamberlain, 1984). We follow Suri (2006) and expand the method to accommodate three years of data. The estimation procedure is automated in a new Stata module (Barriga Cabanillas et al., 2018). The approach, which is structural in nature, uses a set of reduced-form parameters to recover the structural parameters of interest using an optimal minimum distance estimator.

The structural approach to identifying the CRC model has several advantages over an instrumental variables approach. First, it does not require the selection of an instrument and defence of the exclusion restriction. Rather, identification relies on a linear projection of the individual's rate of return onto his or her history of adoption. This is similar to the correlated random effects method, which has become a staple of panel data analysis. Second, the approach allows the researcher to test how important a role an individual's rate of return plays in the adoption decision. Third, the approach allows us to recover the distribution of the rate of return for post-estimation analysis. All are improvements over the traditional way of estimating CRC models with instrumental variables.

6.4 Results

We begin by estimating a series of models that impose homogeneity in the returns to improved chickpea. These include basic OLS regressions as well as fixed effects (FE) regressions designed to control for unobserved heterogeneity uncorrelated with the adoption decision. Next, we estimate a CRE model to help fix ideas on how we estimate the CRC model. We also provide descriptive evidence on the existence of heterogeneity in the returns to adoption by estimating the returns to improved chickpea adoption based on observables. Finally, we estimate several specifications of the CRC model and use the structural estimates to recover the comparative advantage.

We estimate a Cobb-Douglas generalized yield function with log of chickpea yield as the dependent variable.[21] However, our primary interest is in estimating generalized revenue and profit functions in which revenue is measured as gross revenue per hectare and profit as net income per capita. These specifications directly embed our production function, with the Cobb-Douglas framework underpinning the revenue or profit function. Households, when making their technology adoption decisions, are maximizing over these revenue or profit functions for which the Cobb-Douglas technology is an input.[22]

6.4.1 OLS, FE and returns on observables

We begin by estimating OLS and fixed effects versions of the production, revenue and profit functions with various sets of controls (see Table 6.5). In all of the OLS regressions, the returns to adoption are positive and significant. Returns to adoption range between 12 and 46 percent depending on how we measure returns (see columns (1)-(2), (5)-(6) and (9)-(10)). The inclusion of district level controls and measured inputs reduces the returns to adoption but the returns remain positive and significant. These results provide suggestive evidence that heterogeneity exists at the district level but that differences in environment and access to improved inputs does not fully explain the heterogeneity.

When we include household fixed effects, returns to adoption decrease and now range between 4 and 29 percent (see columns (3)-(4), (7)-(8) and (11)-(12)). In the case of yields, the returns to adoption are no longer significantly different from zero. Comparably, the returns in terms of gross revenue and net income remain positive and significant. We take this as evidence that households are not adopting improved chickpea for their potential yield gains. Rather, households adopt improved chickpea for the potentially positive and significant returns gained as measured by revenue and income. This suggests the need to consider economic returns, not purely physical returns, when seeking to understand the technology adoption decisions among smallholder farmers.

While heterogeneity in returns clearly exists in our data, much of it is a function of input use decisions, regional environmental differences, or time-invariant differences across households (i.e., the absolute advantage). Anywhere between half and all of the returns to adoption can be explained through the inclusion of either observables or controlling for unobservables. The one caveat of our interpretation of the OLS and fixed effects results is that estimation of the equations relies on a fairly restrictive assumption regarding the adoption process. Fixed effects is a special case of the CRE and CRC models which assumes the comparative advantage term is equal to zero. This assumption amounts to requiring that a household's experience or history of adoption has no effect on the outcome of interest, or that the effect is the same in every period. Alternatively, if households are fully aware, or ignorant, of the potential gains from adoption, it may be the case that their history of adoption has a time-invariant impact on their returns. Given that nearly 40 percent of the households in the sample do not change their adoption status, such an assumption may be reasonable.

[21] We use the inverse hyperbolic sine transformation to convert levels to logarithmic values.
[22] See Suri (2011) for more details on the connection between the adoption decision, the necessary assumptions for profit maximization and the connection to our production framework.

Table 6.5 Basic OLS and household FE specifications

	Ln chickpea yield (kg/ha)				Ln gross revenue (USD/ha)				Ln net income per capita (USD)			
	OLS	OLS	FE	FE	OLS	OLS	FE	FE	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Improved chickpea (1 = yes)	0.113*	0.010	−0.049	−0.052	0.117***	0.109***	0.091***	0.063**	0.445***	0.416***	0.274***	0.262***
	(0.060)	(0.060)	(0.077)	(0.075)	(0.024)	(0.023)	(0.029)	(0.028)	(0.062)	(0.061)	(0.072)	(0.072)
Ln seed (USD/ha)		0.125***		0.103**		0.060***		0.044**		−0.106**		−0.124**
		(0.034)		(0.042)		(0.018)		(0.021)		(0.047)		(0.055)
Ln fertiliser (kg/ha)		−0.001		−0.013		0.007		0.012		−0.050**		−0.036
		(0.017)		(0.021)		(0.007)		(0.009)		(0.020)		(0.022)
Ln chemicals (USD/ha)		0.048***		0.043***		0.026***		0.028***		0.044***		0.027
		(0.012)		(0.014)		(0.006)		(0.008)		(0.017)		(0.020)
Ln family labour (days/ha)		0.232***		0.253***		0.066***		0.069***		−0.001		0.043
		(0.031)		(0.039)		(0.013)		(0.016)		(0.035)		(0.041)
Ln hired labour (USD/ha)		0.003		0.002		0.019***		0.017***		0.027**		−0.000
		(0.009)		(0.012)		(0.004)		(0.005)		(0.011)		(0.014)
Ln land preparation (USD/ha)		0.079		0.028		0.008		−0.013		−0.001		−0.024
		(0.056)		(0.067)		(0.016)		(0.019)		(0.044)		(0.050)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
District Controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Household FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1,011	1,011	1,011	1,011	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800
R2	0.050	0.178	0.002	0.087	0.084	0.257	0.063	0.206	0.054	0.185	0.046	0.120

Note: Dependent variable is either log of chickpea yield, log of gross revenue, or log of income per capita. In specifications in which the dependent variable is measured in dollar terms, we convert relevant independent variables to value terms. Additional household controls include gender of household head, household size, dependency ratio, off-farm income, land ownership, age of household head, education of household head, log of distance to market, average rainfall for the past five years, rainfall shock index and dummies for soil quality. Standard errors are reported in parentheses (* p<0.1; ** p<0.05; *** p<0.01).

To provide further evidence of heterogeneity to returns, at least on observables, we next regress our measures of returns on observables separately by adoption status (see Table 6.6). In a majority of cases the covariates do not differ in significance across adoption status. The only input for which we see consistent differences is the use of chemicals. There are never any significant returns to chemical use for households cultivating local varieties of chickpea. Conversely, returns to chemicals are always positive and significant for households cultivating improved varieties. This result provides further evidence that the choice to purchase chemicals may be made jointly with the decision to adopt improved varieties. If this is the case, chemical use may be correlated with the comparative advantage term and this endogeneity will need to be controlled for in the CRC model.[23]

Table 6.6 Heterogeneity by observables

	Ln chickpea yield (kg/ha)		Ln gross revenue (USD/ha)		Ln net income per capita (USD)	
	Local	Improved	Local	Improved	Local	Improved
Ln seed (USD/ha)	0.149	0.137**	0.006	0.165***	−0.087	−0.101
	(0.090)	(0.059)	(0.036)	(0.050)	(0.115)	(0.091)
Ln fertiliser (USD/ha)	0.008	−0.025	0.028	0.009	−0.003	−0.060**
	(0.083)	(0.018)	(0.022)	(0.015)	(0.071)	(0.027)
Ln chemicals (USD/ha)	0.040	0.029**	0.019	0.039***	0.040	0.055***
	(0.054)	(0.014)	(0.018)	(0.011)	(0.057)	(0.021)
Ln family labour (days/ha)	0.108	0.302***	0.082**	0.053**	0.008	0.054
	(0.109)	(0.041)	(0.037)	(0.022)	(0.120)	(0.040)
Ln hired labour (USD/ha)	−0.024	0.012	0.020	0.028***	−0.043	0.021
	(0.052)	(0.011)	(0.013)	(0.008)	(0.041)	(0.014)
Ln land preparation (USD/ha)	0.042	0.149	−0.050	0.036	0.008	0.078
	(0.127)	(0.117)	(0.039)	(0.045)	(0.124)	(0.082)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276	735	760	1,040	760	1,040
R2	0.174	0.203	0.167	0.260	0.096	0.242

Note: Dependent variable is either log of chickpea yield, log of gross return per hectare, or log of income per capita. Additional household controls include gender of household head, household size, dependency ratio, off-farm income, land ownership, age of household head, education of household head, log of distance to market, average rainfall for the past five years, rainfall shock index and dummies for soil quality. Standard errors are reported in parentheses (∗ $p<0.1$; ∗∗ $p<0.05$; ∗∗∗ $p<0.01$).

6.4.2 CRE and CRC

To test the assumption that the history of adoption has either no effect or a time-invariant effect on returns, we next estimate a CRE model (see Table 6.7). To do this, we replace the time-invariant household fixed effect with its projection on the complete household history of adoption. Coefficients on the return to adoption are similar in the CRE model when compared to the fixed effect model. Returns on yield are not significant while returns on gross revenue per hectare and on income per capita are positive and significant.

[23] In the current draft of this paper, we have yet to implement the three year CRC model with endogenous regressors. In subsequent drafts we expect to fully control for this potential source of endogeneity

Table 6.7 CRE reduced form and structural estimates

	Ln chickpea yield (kg/ha)						Ln gross revenue (USD/ha)						Ln net income per capita (USD)					
	Reduced Form Estimates																	
	Without covariates			With covariates			Without covariates			With covariates			Without covariates			With covariates		
	2007	2010	2014	2007	2010	2014	2007	2010	2014	2007	2010	2014	2007	2010	2014	2007	2010	2014
Improved,	0.102	0.154***	0.222**	−0.040	−0.076	0.122	0.152***	0.182***	0.061*	0.144***	−0.024	0.043	0.370***	0.346***	0.397***	0.446***	0.068	0.364***
2007	(0.078)	(0.060)	(0.105)	(0.080)	(0.059)	(0.117)	(0.031)	(0.049)	(0.035)	(0.031)	(0.042)	(0.035)	(0.060)	(0.110)	(0.123)	(0.051)	(0.109)	(0.130)
Improved,	0.044	0.023	−0.012	0.038	0.144**	−0.099	0.007	0.127***	−0.046	0.025	0.164***	−0.048	0.030	0.379***	−0.051	0.050	0.395***	−0.143
2010	(0.101)	(0.077)	(0.136)	(0.097)	(0.072)	(0.142)	(0.030)	(0.047)	(0.034)	(0.031)	(0.042)	(0.035)	(0.058)	(0.107)	(0.120)	(0.051)	(0.109)	(0.130)
Improved,	0.425***	0.131	0.306*	0.241	0.278**	0.007	0.129***	−0.028	0.136***	0.051	0.106**	0.036	0.051	0.138	0.570***	0.028	0.299**	0.255
2014	(0.128)	(0.098)	(0.173)	(0.148)	(0.109)	(0.215)	(0.036)	(0.055)	(0.040)	(0.038)	(0.052)	(0.043)	(0.068)	(0.125)	(0.140)	(0.063)	(0.134)	(0.160)

Optimal Minimum Distance (OMD) Structural Estimates

	Without covariates	With covariates	Without covariates	With covariates	Without covariates	With covariates
β	-0.041	0.032	0.078***	0.101***	0.226***	0.282***
	(0.074)	(0.073)	(0.030)	(0.028)	(0.076)	(0.073)
λ1	0.163***	-0.046	0.090***	0.028	0.222***	0.171**
	(0.049)	(0.050)	(0.025)	(0.024)	(0.069)	(0.069)
λ2	0.045	0.060	-0.004	0.009	0.041	0.039
	(0.068)	(0.067)	(0.022)	(0.022)	(0.050)	(0.046)
λ3	0.259***	0.224***	0.074***	0.025	0.113**	0.066
	(0.072)	(0.082)	(0.027)	(0.027)	(0.056)	(0.055)
Observations	1,011	1,011	1,800	1,800	1,800	1,800
χ^2	1,472**	1,986***	8,604***	8,525***	7,641***	5,126***

Note: Dependent variable is either log of chickpea yield, log of gross return per hectare, or log of income per capita. For specifications with covariates, these include log seed, log fertiliser, log chemicals, log family labour, log hired labour, log land preparation costs, gender of household head, household size, dependency ratio, off-farm income, land ownership, age of household head, education of household head, log of distance to market, average rainfall for the past five years, rainfall shock index and dummies for soil quality. Standard errors are reported in parentheses (*p<0.1; **p<0.05; ***p<0.01).

While the CRE and fixed effects estimates of returns are similar, the χ^2 values on the overidentification tests allow us to reject the fixed effects model in all cases. However, the overidentification test is an omnibus test, meaning that it has low power to reject any specific alternative. Thus, our ability to reject the fixed effects model is not particularly surprising.

A more powerful test can be constructed using the CRC model. Here we not only estimate the returns to adoption, but the degree of selection due to heterogeneity in households' comparative advantage (φ). A t-test on the φ term is a test of the validity of the fixed effects assumption that unobserved heterogeneity is time-invariant and uncorrelated with the decision to adopt or the experience of adoption.

Table 6.8 reports only the OMD estimates of the structural parameters from the CRC model. The CRC estimates of the returns to adoption are similar to both the CRE and fixed effects estimates. Returns to adoption for yields are again not significant once we have controlled for observables and unobservables. Returns on gross revenue are greater in the CRC model compared to the CRE and fixed effects models, while returns on income per capita are less in the CRC model compared to the CRE and fixed effects models.

Table 6.8 Three year CRC OMD structural estimates

	Ln chickpea yield (kg/ha)		Ln gross revenue (USD/ha)		Ln net income per capita (USD)	
	Without covariates	With covariates	Without covariates	With covariates	Without covariates	With covariates
β	0.074	0.022	0.237***	0.317***	0.230***	0.242**
	(0.247)	(0.068)	(0.081)	(0.104)	(0.078)	(0.111)
φ	6.386	0.966	0.619	2.475	−0.234	−0.566
	(17.59)	(1.781)	(1.052)	(4.077)	(0.595)	(0.459)
λ_1	0.237	−0.022	0.109	0.029	0.637**	0.368
	(0.155)	(0.185)	(0.203)	(0.166)	(0.278)	(0.269)
λ_2	0.300***	0.180	0.263*	0.167	0.389***	0.265***
	(0.109)	(0.114)	(0.140)	(0.120)	(0.109)	(0.093)
λ_3	0.273***	0.150	0.276**	0.102	0.267***	0.150**
	(0.104)	(0.112)	(0.111)	(0.117)	(0.080)	(0.074)
λ_4	−0.298**	−0.258	−0.295	−0.254	−0.895**	−0.712
	(0.121)	(0.224)	(0.242)	(0.220)	(0.418)	(0.451)
λ_5	−0.180	0.052	0.079	0.015	−0.336	−0.132
	(0.265)	(0.207)	(0.259)	(0.198)	(0.278)	(0.307)
λ_6	−0.284***	−0.120	−0.130	−0.098	−0.406***	−0.299***
	(0.103)	(0.121)	(0.168)	(0.117)	(0.127)	(0.107)
λ_7	0.267**	0.207	0.190	0.185	0.869*	0.904
	(0.123)	(0.223)	(0.263)	(0.184)	(0.464)	(0.667)
Observations	1,014	1,014	1,809	1,809	1,809	1,809
χ^2	4,322***	5,442***	4,682***	6,477***	8,816***	8,519***

Note: Dependent variable is either log of chickpea yield, log of gross return per hectare, or log of income per capita. The structural coefficients are the average return (β), the comparative advantage coefficient (φ) and the projection coefficients (λ_i). For specifications with covariates, these include log seed, log fertiliser, log chemical, log family labour, log hired labour, log land preparation costs, gender of household head, household size, dependency ratio, off-farm income, land ownership, age of household head, education of household head, log of distance to market, average rainfall for the past five years, rainfall shock index and dummies for soil quality. Standard errors are reported in parentheses (* $p<0.1$; ** $p<0.05$; *** $p<0.01$).

Somewhat surprisingly, the estimates of φ are not statistically different from zero, though the point estimates are positive. If we believe that $\varphi = 0$, this implies that selection into improved varieties is not based on any sort of unobserved comparative advantage. Intuitively, heterogeneity exists between households in that some households will be better farmers than other households, regardless of crop type. This absolute advantage in farming is completely controlled for by the fixed effects model. What the CRC results show is that there appears to be no detectable additional comparative advantage which makes some farmers better at cultivating improved varieties compared to local varieties and results in their selecting into improved varieties.

In order to test the robustness of our three year results, we adopt Suri's (2011) simpler two year model and estimate each two year pair. Given that adoption rates were so high during the period 2007 to 2010 it may be that case that our φ is significant for that period but insignificant as the speed of adoption slows down. Or we might expect significant results over the longer time period 2007 to 2014. Table 6.9 displays the results from these pairwise regressions.

Table 6.9 Two year CRC OMD structural estimates

	Ln chickpea yield (kg/ha)			Ln gross revenue (USD/ha)			Ln net income per capita (USD)		
	2007-10	2010-14	2008-14	2007-10	2010-14	2008-14	2007-10	2010-14	2008-14
β	0.041	−0.523	−0.128	0.172**	0.058	−47.93***	0.433***	−20.12***	−0.006
	(0.158)	(3.258)	(0.137)	(0.069)	(0.126)	(0.038)	(0.066)	(0.161)	(0.419)
φ	3.485	−0.877*	0.509	−0.575	−1.535	−1.000***	−1.484**	−1.001***	−0.622
	(12.95)	(0.495)	(2.197)	(1.386)	(1.313)	(0.000)	(0.719)	(0.003)	(0.820)
λ_1	0.025	−0.163	−0.117	−0.031	0.107*	0.123	0.239	0.219	0.291
	(0.126)	(0.270)	(0.333)	(0.080)	(0.062)	(0.090)	(0.205)	(0.225)	(0.335)
λ_2	0.076	0.256**	0.141	0.028	0.046	−0.003	0.014	0.267*	0.014
	(0.092)	(0.126)	(0.143)	(0.032)	(0.055)	(0.036)	(0.055)	(0.150)	(0.068)
λ_3	−0.045	0.985	0.218	−0.045	−0.014	168.19	−0.150	36.762	0.507
	(0.090)	(4.369)	(0.476)	(0.192)	(0.207)	(0.000)	(0.203)	(0.000)	(1.373)
Observations	676	676	676	1,206	1,206	1,206	1,206	1,206	1,206
χ^2	154.9	2,011***	62.24	1.187	7,875***	2,515***	115.0	2,913***	144.5

Note: Dependent variable is either log of chickpea yield, log of gross return per hectare, or log of income per capita. The structural coefficients are the average return (β), the comparative advantage coefficient (φ) and the projection coefficients (λi). All specifications include covariates. These are log seed, log fertiliser, log chemical, log family labour, log hired labour, log land preparation costs, gender of household head, household size, dependency ratio, off-farm income, land ownership, age of household head, education of household head, log of distance to market, average rainfall for the past five years, rainfall shock index and dummies for soil quality. Standard errors are reported in parentheses (* $p<0.1$; ** $p<0.05$; *** $p<0.01$).

The majority of estimates of φ are not significant. Again, returns to improved chickpea yields are never significantly different from local varieties. However, estimates of φ are significant and negative for gross revenue during the period 2007 to 2014 as well as for income per capita during the period 2007 to 2010. In both cases φ is negative, indicating that households which are, on average, better farmers receive lower returns to improved varieties. This is equivalent to stating that below average farming households that adopt improved varieties are able to close the production gap with above average farming households.

While far from robust, our two year results do support Suri's (2011) hypothesis. However, the larger question remains: why in the vast majority of cases do we find no selection into improved varieties based on a household's comparative advantage? There could be several explanations for our null result. First, is that our rich set of control variables has completely controlled for any comparative advantage that might remain unobservable if we had fewer controls. This seems unlikely since our results do not differ dramatically when we exclude/include covariates from our model. Second, our estimates may be too imprecise, meaning that a comparative advantage exists but we lack the power to detect it. Third, the skill and knowledge to cultivate improved varieties is extremely similar to that required to cultivate local varieties. If this is the case, no special advantage is required to shift a household from non-adoption to adoption. Given the relative simplicity of cultivating chickpeas, this explanation is plausible. Finally, it may be that economic returns to improved varieties are so consistently large that it is rational for every household to adopt. Given the high adoption rates and that we consistently find average returns to adoption to range between 10 and 40 percent, we believe this explanation is the most plausible. Additionally, this explanation does not preclude the existence of selection based on comparative advantage. Rather, what it says is that during this stage of the adoption cycle, the returns gained by all households from adoption greatly exceed any comparative advantage that some households might gain. If we were early or later in the adoption cycle, there may have been more sorting based on a household's comparative advantage.

We conclude that comparative advantage might be an important factor in determining adoption of technologies with lower average returns, such as maize and fertiliser in Suri (2011). However, for technologies with large returns, such as the case of improved chickpea in Ethiopia, individual comparative advantage may not matter when measured against the absolute advantage all households would gain from adoption.

6.5 Conclusions and policy implications

Studies of agricultural technology adoption have focused on the physical returns (yields) that new technology provides. This has created an empirical puzzle in which households choose not to adopt despite potential yield gains. Numerous potential solutions have been posed, each of which contain elements to commend itself to the policymaker.

We propose an alternative solution focused on economic returns to new technologies. We study a technology that appears to have no impact on yields yet has been widely adopted. Using three years of panel data and a correlated random coefficient model we calculate the returns to improved chickpea adoption in terms of yields, gross revenue and net income. Across a number of specifications we find no evidence that adoption results in improved yields. However, we do find evidence that adoption results in significant positive returns to gross revenue and net income. Somewhat surprisingly, we find no evidence of comparative advantage or heterogeneity in returns based on unobservables.

We conclude that any comparative advantage some farmer may possess is dominated by the clear advantage available to all farmers from adoption. This explains the high adoption rates (up to 80 percent) despite the lack of yield gains. Thus, we conclude that the large economic benefits of improved chickpea drives the adoption decision.

Our results imply that the divergent adoption rates across contexts may be explained by the quality of the markets for the output. Persistent low adoption rates of improved maize varieties that have been documented across Eastern Africa may be the result of a lack of markets where farmers can sell their surpluses. This suggests that policy focused on developing further genetic gains in terms of yields may be misguided. Without complementary economic gains, which require markets for surpluses, increase physical gains will likely be unattractive to potential adopters.

The context of our study is an extreme example of the extent to which markets matter. Despite the new technology providing no statistically significant gains in yield, adoption of the technology has been extremely high. This adoption success has been the result of existing markets for the improved varieties in which farmers can market their surplus and reap economic benefits unavailable from growing and marketing less desirable traditional varieties. Policy and future research should reorient in a direction that considers both the physical and the economic returns as factors that influence the adoption of agricultural technologies.

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Chapter 7

Discussion and conclusions

7

7.1 Key lessons

Key lessons learnt are organized around the various meanings behind the title 'poor farmers'. First, 'poor farmers' refers to the welfare status (poverty) of households and potential of agricultural innovations to improve this. Second, 'poor farmers' denotes the heterogeneity and possible agricultural underperformance of rural households compared to their neighbours. Third, 'poor farmers' refers to a sad reality wherein 'poor farmers' are unable to access and benefit from available agricultural innovations. Finally, the title 'poor farmers' was inspired by and is a playful nod to the book 'Poor Economics' (Banerjee & Duflo, 2012).

7.1.1 Poor farmers I: Agriculture's potential contribution to smallholder welfare

The prevalence of poverty and potential of improved technology to increase food production highlights the importance of supporting 'poor farmers' in sub-Saharan Africa. A large part of African agricultural production originates from poor farmers (Burney & Naylor, 2012; Pretty et al., 2011). Rural households in the region are among the poorest and food insecure people in the world (OECD/FAO, 2016). At the same time, rapid population growth calls for increased food production (Ricker-Gilbert et al., 2014). As the limits of agricultural extensification in many African countries have been reached there has been a call for agricultural intensification through the adoption of improved technology.

Agricultural innovations offer considerable promise for rural Africa in the face of large and persistent yield-gaps (Dzanku et al., 2015; Tittonell & Giller, 2013). Increasing the adoption of technology by smallholder farmers is therefore considered an important intervention for meeting development goals like the SDGs (United Nations, 2015). Accordingly, improving the performance of African smallholders has been put forward as a potential win-win intervention to solve the dual problems of poverty and hunger (Dercon et al., 2009). At the same time, there are doubts about how millions of smallholder farm households will feed themselves while generating enough surplus to feed the non-agricultural population (Ricker-Gilbert et al., 2014). So, to what extent can agricultural innovations contribute to improving the welfare of 'poor farmers'?

The case of improved chickpea in Ethiopia shows that new technology in the form of improved varieties had a positive impact on income. However, it also shows that in situations of extra-ordinary high inflation, technology adoption does not necessarily prevent households from becoming poor. Technology adoption is a complex process, where many pre-conditions have to be met. The districts studied in Ethiopia were characterized by a conducive agro-ecological climate for chickpea cultivation, while farmers operated large landholdings and depended on farming for the mainstay of their livelihoods. Farmers also had good market and extension access. All this facilitated adoption and translated into a positive impact on farmer welfare. This suggests that new technology should offer attractive benefits while avoiding negative trade-offs.

In the case of Kenya, the relation between intensification and poverty was studied in high and low-potential districts. Both districts, however, were characterized by relatively small land sizes and diversified livelihoods. Full-time farmers in the high-potential area generated sufficient returns from farming to earn incomes above the poverty line. By contrast, most households in the low-potential area failed to derive sufficient income from farming and were forced into low-return non-farm activities. Diversified mixed households also generated considerable returns from farming, suggesting that farm and off-farm activities need not be opposing. Nonetheless, it seemed unlikely that technology transfer would improve the welfare of the comparatively well-off non-farm and resource-poor farm-worker households in Kenya. This thesis thus provides examples of both the potential and limits of agricultural technology transfer's contribution to rural welfare.

7.1.2 Poor farmers II: Differences in the potential for agricultural intensification

Do Africa's large yield gaps and stagnant crop productivity mean that African smallholders are 'poor farmers'? Low mean yields mask considerable variation in productivity across countries, regions and even districts (Jayne et al., 2010). Moreover, there is a continuing debate on whether there is an inverse farm size and productivity relationship in Africa. In fact, evidence suggests that smallholders are more productive, with yields falling as the scale of production rises (Carletto et al., 2013; Larson et al., 2014). However, a recent study indicates that this inverse relationship may be the result of measurement errors in self-reported production (Desiere & Jolliffe, 2018). Others even dubbed African smallholders as 'reluctant micro-entrepreneurs' whose underperformance resulted in the region's continued divergence from global agricultural performance (Collier & Dercon, 2014). My findings suggest that some households are considerably better at farming than others in the same location. It may not be appropriate to call underperforming households 'poor farmers', however, it feels safe to conclude that some perform less well than their neighbours.

Differences in the aspirations of rural households can influence their agricultural performance. In the case of Kenya, all households adopted technology but they did not enjoy the same benefits. Two groups, out of four, underperformed for distinct reasons. So-called farm-worker households were the poorest, both in terms of poverty and farming. Their poor farming can be partly contributed to their limited resource base. This prevents them from investing in agricultural technology and creates a chronic poverty trap of nutrient mining on degraded soils (Tittonell & Giller, 2013). In addition, farm-workers have to sell their labour to earn a living, leaving limited time to work on their own plots. As such, their labour is sold cheaply to wealthier farmers, thereby reinforcing the gap between both (Tittonell, 2007). When improved varieties are offered to these households they may end up selling or consuming them. Rather than providing farm-workers with agricultural innovations, they may be better served through cash transfers or safety nets.

The second group of underperforming farmers, dubbed non-farm households, were the wealthiest group but had similar yields and returns to poor farm-workers. These households largely depend on non-farm wage labour or self-employment for their income. They may engage in farming to spread income risks (Banerjee & Duflo, 2007) or because of a cultural attachment to agriculture as a way of life (Barrett et al., 2001). These part-time farmers, however, will not put the same level of effort into farming as those whose livelihoods depend on it. Indeed, despite similar hybrid seed and chemical fertiliser application rates, non-farm household maize yields and returns were considerably lower than those of full-time farmer and mixed income households. Since non-farm households are poor at farming but non-poor otherwise, providing them with agricultural innovations does not contribute to food security or poverty reduction.

This thesis also evidences that many rural African households are very good at farming and are not ‘poor farmers’ at all. Full-time farmers and mixed income households in Kenya had relatively high yields and farm returns. This may be indicative of their continued interest to invest in agriculture. Indeed, technology adoption rates were significantly higher than those of farm-worker and non-farm households. These innovative, ambitious and market-oriented farmers stand in stark contrast with the commonly conveyed image of poor ‘subsistence’ farmers. Agricultural interventions should try to target these better-performing farmers and tailor technologies to their needs. However, it may be difficult to target them as many rural households self-identify as farmers.

Ethiopian households in the study area were almost exclusively focused on farming, with crop income constituting an average of 90 percent of total income. Their high yields and returns suggest that rural households with a continued interest in farming can benefit from agricultural innovations. Indeed, the dramatic increase in uptake of improved chickpea and its positive impact on household welfare show the promise of well-targeted and appropriate agricultural innovations. In addition, our analysis of returns to improved chickpea found no evidence of heterogeneous performance among farmers, which is in contrast to the Kenyan case.

It is not clear to what extent Ethiopian household’s continued investment in agriculture is the result of aspirations or the outcome of limited alternative opportunities. During FGDs Ethiopian farmers indeed indicated that there were limited off-farm opportunities. Many said that increasing population-density left insufficient land, forcing youth to seek employment in urban areas. Despite diversified livelihoods, many Kenyan households self-identified as farmers and aspired to increase their agricultural income and activities. Nonetheless, very few aspired a future for their children in farming. These dynamics present interesting challenges and future research topics.

7.1.3 Poor farmers III: The need to improve agricultural research for development

Poor targeting and insufficient attention to the attractiveness of innovations limit smallholder access and benefits from available improved technology. Sadly, the transfer of technologies to ‘poor farmers’ by agricultural research for development is far from optimal. This is evidenced by continued low technology adoption levels (World Bank, 2015c), persistent yield gaps (Tittonell & Giller, 2013) and the limited success in sparking an African Green Revolution (Otsuka & Kijima, 2010). It thus seems that there is considerable scope to improve efforts to better serve these ‘poor farmers’.

This is not to say that the agricultural research community has not contributed to smallholder welfare in Africa. Indeed, many studies cite high social returns on investments of agricultural research (e.g., Renkow & Byerlee, 2010). Moreover, an increasing number of studies shows a positive impact of improved technology on smallholder welfare (Bezu et al., 2014; Mathenge et al., 2014; Smale & Mason, 2014; Stewart et al., 2014). Similarly, findings in this thesis showed the positive impact of improved chickpea adoption on smallholder welfare in Ethiopia. The case also showed that improved technology can be rapidly adopted when certain conditions are met. The Kenyan case study also showed farmers growing their way out of poverty using various innovations. However, rampant rural poverty, food insecurity and an increasing global population all suggest the urgency of improving agricultural development efforts.

Part of the problem may be that international agricultural research centres are driven by the need to generate funding while showing impact to warrant these investments. This has led to an irreconcilable portrayal of African smallholders as poor food-insecure under-adopters who, at the same time, greatly benefit from agricultural research as suggested by high-returns to investments. This has created a situation that is definitely not in the best interest of these 'poor farmers'. At the same time, development resources are scarce and the plight of the rural poor demands the identification of the most cost-effective way of reducing poverty. Agricultural researchers and partners need to work together better to identify attractive technologies with the potential to end poverty and hunger.

Saying that the adoption of technology is low implies an expectation that adoption should indeed take place (Sumberg, 2005). Indeed, to expect every innovation to be widely adopted is unrealistic. Selecting the right agricultural innovations for scaling is not an easy task. Manifold trade-offs have to be taken into account to determine the attractiveness of technology for intended users in a specific context. For instance, land and labour allocations are difficult to assign to specific technologies, while prices of inputs and outputs are unstable and unpredictable. Foster and Rosenzweig (2010) indicated that this complexity explains why many studies fail to carefully reconstruct the net returns to adoption. Moreover, even profitable technology may not be adopted if it does not meet the needs, aspirations and context of intended users. Still, the dramatic uptake of improved chickpea in Ethiopia suggests the potential of finding the right fit of innovation, user and context.

I tried to avoid common pitfalls of adoption studies by applying a farming systems perspective. Both the Kenyan and Ethiopian case studies collected data on farm and non-farm income generating activities. In Kenya, this provided important information to explain the diverging agricultural performance of households against a range of intensification indicators. The Ethiopia case study moved beyond common dichotomous and static conceptions of adoption by capturing adoption and dis-adoption over time as well as the intensity of adoption. It also compared chickpea types, varieties and other crops grown. Finally, this thesis aimed to move beyond a narrow focus on constraints, which is often used to explain the under-adoption of innovations. Examples of such constraints are poor infrastructure, limited market access or even unavailability of the technology itself. Evidently all important determinants of adoption. Sumberg (2005) thus rightly indicates that for agricultural researchers to continue to suggest that their innovations are not being adopted because of well-known constraints, is to deny their role in and responsibility for the agricultural research for development process.

In the end, robust evidence generated by experiments on what works, where and why, can be vastly instrumental in effectively assisting 'poor farmers' while securing investments. This may also help address the bias of agricultural research centres to promote their mandate crops and of breeders to promote their own varieties. Thus, there is a need for more experimental studies to rigorously assess the impact of available technologies in real world settings. In addition, future interventions should include an ex ante focus on the farm and farming system level to achieve appropriate targeting of technologies (Giller et al., 2011). Careful and independent screening of innovations will hopefully enable the selection of those with most potential for adoption and improvement of farmer welfare. In the next section I provide additional suggestions for future research to better fit the needs of rural smallholders.

7.2 Limitations of the study and avenues for future research

Certain characteristics of the data collected and methods applied may limit the representativeness of my findings. For example, assessing the impact of improved chickpea adoption in Ethiopia using a non-experimental design could be considered less rigorous than a randomized control trial (RCT). The case for experimental studies is convincingly made by Banerjee and Duflo (2012) in 'Poor Economics', which inspired the title of this thesis. Though the methods applied should take away any concerns on rigour, this experience did show me that quasi-experimental evaluations are as expensive and certainly not less cumbersome than experiments. Indeed, measuring impact using an RCT requires less assumptions, econometric expertise and time spent on analysis. In fact, there seem to be few convincing arguments in favour of non-experimental studies. I therefore find it surprising that measuring the impact of agricultural innovations in realistic off-station settings, if done at all, generally relies on quasi-experimental research. As does this thesis.

It is time to move beyond yields and adoption constraints. This thesis shows the importance of carefully measuring benefits and costs associated with new technology to explain adoption decisions. Indeed, more attention should be paid to assessing the attractiveness of innovations in local contexts. Adoption studies should adopt a farm systems perspective and move beyond binary conceptions of adoption by incorporating the intensity and fluidity of adoption. Similarly, the portrayal of rural people as poor farmers eager to adopt and grow their way out of poverty needs to be nuanced. For example, by paying attention to both on and off-farm activities in adoption studies. Additional insight into household adoption decision-making processes may be particularly derived through behavioural research, such as lab-in-the field and discrete choice experiments. Another interesting avenue for future research is testing how better-performing farmers may be identified and targeted by technology transfer interventions. Finally, further research is required to explore findings on livelihood aspirations and the relation between diversification and intensification.

One thesis based on two country case studies cannot provide a conclusive answer on the potential contribution of technology transfer to poverty reduction in sub-Saharan Africa. It has been suggested that the debate on the role of small farms in poverty alleviation has remained unresolved because key relationships are context dependent (Gebremedhin et al., 2009). So to what extent can the results presented in this thesis be generalized? The literature regularly highlights the heterogeneity in African farming systems, livelihood aspirations, institutions, agro-ecology, etcetera. In this thesis, I build on this work and differentiate farmers with different livelihood aspirations in Kenya. I also noted the importance of appropriate targeting of interventions to fit the right agro-ecological and market context in Ethiopia. The findings show that matching innovations with context is crucial for success. Moreover, findings on the impact of chickpea in the Shewa region cannot be generalized to the rest of the country, let alone sub-Saharan Africa. Similarly, I do not assume that the livelihood aspirations captured in Embu and Kitui are necessarily representative for Kenya. However, there has to be a limit to context-dependence when trying to assist smallholder farmers.

Besides many crucial differences there are many similarities in rural aspirations and contexts. Instead of drilling down to minute differences, future work may be better directed at scoping similarities to identify scaling opportunities and improve targeting of agricultural innovations. Poor farmers are doing the best they can to survive, facing countless trade-offs in an unpredictable environment. Evidently, they are not willing to take large risks by adopting unknown innovations with marginal benefits and possible disadvantages. *Ceteris paribus* most rural households prefer technologies with higher returns, net of inputs and labour. I hope that this thesis has made a valid case to move beyond yields and pay more attention to this important determinant of technology adoption and impact. Only innovations that substantially outperform locally available technologies and feature limited downside risks are likely to be adopted on a large scale. Hence, technology transfer interventions should conduct ex-ante analyses prior to piloting and performing ex-post (experimental) impact assessment prior scaling. I believe that these lessons are applicable for smallholders across Africa.

7.3 Conclusions

There is not a simple answer to the question whether technology adoption can contribute to poverty reduction. My research indicates that there is certainly potential for smallholder farmers to benefit from technology adoption. However, this is highly dependent on finding the right fit of technology, household and context. My findings also lead to certain pertinent questions: Are all rural households best served by improved agricultural technology? Where only some households (or regions) can be assisted, should interventions target certain households to generate the biggest impact? And, what should this impact be; decreased poverty or increased food production?

There may be trade-offs between the dual goals of ending poverty and hunger. When targeting interventions there may be a need to distinguish between ‘poor farmers’, in terms of household welfare, and ‘poor farmers’, in terms of agricultural performance. For example, farm-workers were both in terms of farming and welfare the poorest households. To eradicate poverty, development interventions could focus on supporting these households. However, supporting them with new agricultural technology may not be the most efficient way to increase food production. Similarly, agricultural interventions may improve household welfare but not productivity. For instance, improved chickpea varieties contributed to farmer welfare in Ethiopia but were not necessarily more productive when controlling for inputs and labour.

A related issue is whether smallholder farming is the most efficient way to provide sufficient food for an increasing global population. More specifically, how should smallholders be involved in ‘ending hunger’, if at all? If poverty is to be eradicated rural incomes have to rise. Accordingly, expected returns from agriculture should increase for rural households to remain interested in improving their agricultural performance. Indeed, many households in Kenya are diversifying away from farming and even in Ethiopia many farmers do not foresee a future in farming. Furthermore, few would expect high or middle-income country farmers to survive on a handful of cows and/or less than a hectare of land, as many rural Africans now do. Though smallholder farmers in sub-Saharan Africa need not follow a path akin to agricultural development in other parts of the world, it seems clear that the current trend of farm fragmentation eventually needs to be countered by increased farm consolidation and intensification.

In the meantime, however, there is a burgeoning young rural African population with few alternatives to farming. Moreover, increasing the number of farm-workers through farm consolidation seems a dire prospect given the high prevalence of poverty in this group. Hence, rural households require continued support to ease the transition towards larger scale agriculture, whether through the creation of attractive off-farm opportunities or well-targeted agricultural technology transfer interventions. This thesis thus suggests that ending poverty and hunger can go hand-in-hand, but do not need to, and that agricultural interventions can be justified by either objective. As such, it is neither optimistic nor pessimistic, but aims to be realistic about agriculture’s potential contribution to poverty reduction.

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Summary

Despite decades worth of research there is still much debate on the role of smallholder farmers in agricultural development. This research aims to contribute to insights on the potential of technology transfer interventions to contribute to poverty reduction for smallholder farmers in sub-Saharan Africa, with a focus on Kenya and Ethiopia. By better understanding how farmers decide whether and to what extent to adopt technology, agricultural development projects can be refined to increase their effectiveness.

Chapter 1 provides a general introduction and overview of the adoption literature, introduces the study areas and outlines the objectives, research questions and methodologies applied to answer them. The other chapters are individual publications that form the core part of this thesis.

Chapter 2 explores rainfed agriculture's potential as a pathway from poverty through a comparative study of Embu and Kitui districts in eastern Kenya. It concludes that agricultural intensification appears a pathway from poverty in high-potential rainfed agriculture, while income diversification seems a more realistic strategy in low-potential areas. This highlights the importance of agro-ecological context and livelihood strategies for potential uptake and benefits of new technology.

Chapter 3 explores rural aspirations in Kenya to derive lessons for agricultural innovation and transfer. Though few households specialized in farming, many households self-identified as farmers and aspired to increase their agricultural income. However, few households wanted their children to pursue a future in farming. Combining aspirations with potential to invest, we provide suggestions for targeting agricultural interventions. These findings indicate that we need to start listening better to those people we call 'farmers' to develop and offer innovations that meet their realities.

Chapter 4 studies the conditions that led to the remarkable and rapid spread of improved chickpea varieties in Ethiopia: from 30 to 80 percent of households in seven years. The promotion of an attractive technology suitable for rural Ethiopian households in a conducive environment enabled adoption. This suggests that agricultural development interventions could be improved by paying greater *ex-ante* attention to potential factors of success and failure. This will ensure that agricultural innovations fit the realities and demands of rural households to ultimately design and deploy more successful interventions.

Chapter 5 assesses the impact of improved chickpea adoption on welfare in Ethiopia using three rounds of panel data. Applying a fixed effects instrumental variables approach, predicted area under cultivation from a double hurdle model is used as an instrument for observed area under cultivation. Improved chickpea adoption significantly increases household income while also reducing household poverty. Adoption favoured all but the largest landholders, for who the new technology did not have a significant impact on income. Overall, increasing access to improved chickpea appears a promising pathway for rural development in Ethiopia.

Chapter 6 estimates a correlated random coefficient model to analyse heterogeneity to improved chickpea yields and returns. The technology has been widely adopted, despite limited yield impacts when controlling for observables and heterogeneity. Farmers' comparative advantage was not found to play a significant role in their adoption decisions. It is hypothesized that this is due to the overall high economic returns to adoption. The findings suggest that a focus on yield-increasing technologies may, in some contexts, be misguided.

Chapter 7 discusses the main findings derived from the individual studies, their implications and limitations, and provides suggestions for future research. It juxtaposes the various findings of the two main case studies by exploring the meanings behind the title 'poor farmers'. This shows that it is crucial to distinguish between 'poor farmers', in terms of household welfare, and 'poor farmers', in terms of agricultural performance. My findings suggest that poor farmers can benefit from agricultural research for development interventions, but that this requires the promotion of profitable innovations that fit their context and aspirations.

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At the start of my PhD research, I was staying with a Kenyan-Dutch family in Ngecha, near Nairobi, Kenya. As the family recently started a farming enterprise I wanted to get my host Kamande's view on the proposed topic for my PhD research; the adoption of agricultural innovations by smallholders. He told me that this was great, and that I would learn a lot, but that most of my questions had already been answered. He was right, and I thank him for this humbling insight. I was lucky to be able to stand on the shoulders of giants.

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Simone Verkaart

Simone Verkaart
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
PhD proposal writing	WASS	2013	6.0
ValueLinks: a course on value chain analysis	ValueLinks	2013	1.4
Hands-on GIS for Earth Scientists	Utrecht University	2013	3.0
Advanced statistics modules	PE&RC	2014	2.7
Impact Evaluation for Evidence-Based Policy in Development	University of East Anglia	2014	2.9
Land Dynamics - Getting to the bottom of Mount Kenya	WASS, PE&RC and SENSE	2015	4.0
Introduction to Panel Data Analysis using Stata	Tegemeo	2015	1.4
Introduction to Discrete Choice Experiments	Bangor University	2015	1.4
Experiments in Developing Countries: Methods and Applications	University of Groningen / WUR	2015	2.0
B) General research related competences			
Scientific Publishing	WGS	2013	0.3
Data Management, Analysis and Graphics using Stata	Indepth Research Nairobi	2013	1.1
Using tablets in household surveys: a hands-on introduction using ODK	University of Reading	2014	1.1
The essentials of scientific writing and presenting	WGS	2014	1.2
Working with EndNote	WUR library	2014	0.2
C) Career related competences/personal development			
CGIAR Research Program (CRP) engagement with donors and external stakeholders	CGIAR Consortium Office	2013	3.0
Agricultural technology transfer interventions and poverty reduction in East Africa	GIZ - The Innovation System of Demand Driven Agricultural Research	2013	1.5
The impact of improved chickpea adoption on poverty reduction in Ethiopia	PEGNet - Transformation of Developing and Emerging Economies	2015	1.5
Total			**34.7**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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Cover

A boy chases goats from a chickpea field, Ethiopia, in October 2015. Picture, cover and chapter design by author.