More than adopters: the welfare impacts of farmer innovation in rural Ghana

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Abstract

With the rapidly changing economic environments and numerous challenges hindering smallholders' adoption of externally developed technologies, it is often argued that farmers' innovations may be essential in the livelihoods of rural farm households and need to be promoted. Yet a rigorous assessment of the impacts of farmer innovation is lacking. Consequently, we analyse the effect of farmer innovation on household welfare, measured by farm and household income, consumption expenditure and food security. Using data from a recent field survey of rural farm households in northern Ghana and endogenous switching regression which controls for non-random selection bias, we estimate the welfare gains for innovators from innovating, and non-innovators had they innovated. We find that farmer innovation significantly improves both household income and consumption expenditure for innovators. It also contributes significantly to the reduction of food insecurity among innovative households by increasing household food consumption expenditure, reducing the length of food shortages, and decreasing the severity of hunger. However, we find that the positive productivity and income effects of farmer innovation do not significantly translate into nutritious diet, measured by household dietary diversity. The results also indicate that farmer innovation would have heterogeneous welfare effects for non-innovators, had they decided to innovate. Overall, our results show positive and significant welfare effects of farmer innovation, hence, support increasing arguments on the need to promote farmer innovation as a complement to externally promoted technologies in food security and poverty reduction efforts.

Keywords: Farmer innovation, Endogenous switching regression, Ghana, Household welfare, Impact assessment

1. Introduction

Despite increased food production in the last half-decade, nearly 850 million people (12% of global population) continue to be hungry and food insecure, and many more are micronutrient deficient (Godfray et al. 2010; FAO et al. 2013). Majority of these people live in developing regions, especially Sub-Saharan Africa (FAO et al. 2013). Food insecurity is attributed to a set of complex factors of which climate change is recognised as an important driver (von Braun 2007; Godfray et al. 2010). Climate change poses serious threats to agricultural production and has severe implications for rural poverty and food security (World Bank 2009; Thornton et al. 2011). For instance, climate change affects all the four facets of food security, i.e. availability, access, utilization and stability (Wheeler and von Braun 2013). Smallholder farmers are the mainstay of food production and key to economic growth in developing countries, but they are also one of the most vulnerable to climate change (Easterling et al. 2007). Thus, the challenge of tackling smallholders' food insecurity problems must occur while simultaneously building their resilience to climate change.

The contribution of innovation to agricultural development and rural poverty reduction has been extensively documented (Hayami and Ruttan 1985; de Janvry and Sadoulet 2002). It is also generally agreed that agricultural innovations are essential in addressing the food insecurity and climate change challenges of the world (Brooks and Loevinsohn 2011; Lybbert and Sumner 2012). Such innovations include: seed and agronomic innovations (e.g. improved varieties, fertilizer, and integrated pest management); mechanical innovations (e.g. plough); institutional innovations (e.g. farmer field schools, contract farming and microfinance); biotechnological innovations (e.g. herbicide-resistant crops, tissue culture banana and Bt crops); informational innovations (e.g. mobile phones); and innovations developed by farmers (i.e. grassroot or farmer innovation).

Over the years, there has been increased development and diffusion of technological innovations to farmers, and there are several projects and policy interventions facilitating the adoption of these introduced innovations. With the rapidly changing economic environments, however, local farmers do not only adopt but also generate innovations (Sanginga et al. 2008; Conway and Wilson 2012). They engage in informal experimentation, develop new technologies and modify or adapt external innovations to suit their local environments, and these practices are claimed to play an important role in building their resilience to changing environments and addressing food insecurity challenges (Rej and Waters-Bayer 2001; Kummer et al. 2012). Consequently, there is a growing recognition of the need to promote farmers' innovations and also strengthen their innovative capacities.

The increasing interest in the role of agricultural innovations in reducing poverty, hunger and malnutrition in the world has led to numerous micro-level studies on the impact of agricultural innovation on household welfare in developing countries. Many of these studies (e.g. Kijima et al. 2008; Minten and Barrett 2008; Kassie et al. 2011; Amare et al. 2012;

Asfaw et al. 2012) have shown that agricultural innovations have positive productivity, household income, food security, and poverty reduction effects among adopters. These studies are, however, based on technologies developed and disseminated by National Agricultural Research Institutes (NARI), the Consultative Group on International Agricultural Research (CGIAR) centers and private seed companies, and there is little evidence on the contribution of locally developed farmers' innovation to household's welfare. Considering the numerous challenges hindering poor smallholders adoption of these introduced technologies (Barett et al. 2004), it is argued that innovation generation practices of farm households may also be making impacts in poor people's livelihoods and might form the basis for food security (Waters-Bayer et al. 2006; The Worldwatch Institute 2011). Unfortunately, the few documents on the potential impacts of farmer innovation are only anecdotal, and a rigorous assessment is still lacking. Robust evidences are needed to be able to support increased arguments on the need for policy supports on grassroot or farmer innovation as a complement to introduced technological innovations.

Using survey data from 409 rural farm households in northern Ghana, this study attempts to fill the void on the welfare impacts of farmer innovations. Specifically, we assess the effect of farmer innovation on food and nutrition security, farm and household income, and consumption expenditure. On the one hand, farmers' innovation activities may improve productivity or save labour for non-farm activities and subsequently increase household income and food security. On the other hand, it is possible that the innovation activities may be unsuccessful or do not produce immediate result, hence, has negative effect on household income and food security in the short run. To estimate the treatment effects of farmer innovation, we employ endogenous switching regression which accounts for potential non-random selection bias. We complement the regression results with analysis of farmers' perceived outcomes of their innovations.

This paper contributes to several aspects of the existing literature on the impact of agricultural innovations. Firstly, to the best of our knowledge, this is the first paper to quantitatively and rigorously estimate the impact of farmer innovation on household welfare. Previous studies have focussed largely on externally introduced technologies. Secondly, in measuring household welfare, many studies have used either household income or consumption expenditure as an indicator. However, considering the limitations of both indicators (Deaton 1997), we took advantage of our unique dataset and employ both measures. This allows us to check the robustness of our findings on the well-being effects of farmer innovation. Finally, there are several and varied measures of food security in the literature. For robustness check, we use three different subjective or perception-based measures, in addition to the conventional food consumption expenditure indicator.

Unlike the technological innovation literature, we do not analyse the impact of a single innovation or bundle of innovations. Rather, we consider innovative generation behaviour of farm households. Farmers innovate in diverse ways (ranging from yield to marketing-related) in order to address different challenges; hence, we study the impact of the propensity to generate innovations instead of specific innovations. Thus, we treat the farmers' innovations as farming system innovations which can take several forms. We consider farmer innovation as a process of developing new practices, techniques or products; or modification, adaptation, and experimentation of own or external ideas, by individuals or group of farmers without direct support from external agents or independently of formal research.

The rest of the paper is organised as follows. The next section presents the theoretical model. Here, we look at the agricultural household model. The endogenous switching regression model which we used in estimating the welfare effects of farmer innovation is described in section 3. Section 4 presents the choice of outcome indicators and how they are measured, followed by a presentation of the data and descriptive statistics in Section 5. The empirical results are discussed in section 6, while the last section summarises and concludes the paper.

2. Theoretical model

In order to assess the effect of farmer innovation on household well-being, the farm household model which posits that households maximise utility subject to income, production, and time constraints (Singh et al. 1986) is used as a framework. The model integrates in a single framework, the production, consumption and work decision-making processes of the farm household (Sadoulet and de Janvry 1995). We draw largely from Fernandez-Cornejo et al. (2005) who expanded the model of Huffman (1991) to include technology adoption decisions. In our case, we focus on farmer innovation.

Following Weersink et al. (1998) and Fernandez-Cornejo et al. (2005), households are assumed to derive utility (*U*) from purchased consumption goods (*G*) and leisure (*L*), and the level of utility obtained from *G* and L is affected by exogenous factors such as human capital (*H*) and other household characteristics (*Z*). Thus:

$$Max U = U(G, L; H, Z) \qquad (1)$$

Utility is maximised subject to:

Time constraint: $T = F(I_f) + M + L,\ M \geq 0 \qquad (2)$

Production Constraint: $Q = Q\left[X(I_f), F(I_f), H, I_f, R\right],\ I_f \geq 0 \qquad (3)$

Income constraint: $P_g G = P_q Q - W_x X^{'} + WM^{'} + A \qquad (4)$

The total time endowment (T) of each household is allocated to leisure (L), working on the farm (F), or off-farm work (M). The level of farm output (Q) depends on the quantity of farm inputs (X), the innovativeness of farm household (I_f), F, H, and a vector of exogenous variables that shift the production function (R). X and F are functions of I_f since some of the innovative activities of the farmers are labour or input saving, hence, freeing some time and money for other uses. I_f in turn is determined by households' experience of shocks (S), social capital (S_c), household assets (Ö), risk preference, H and Z. Thus:

$$I_f = I_f(S, H, S_c, R, \ddot{O}, Z) \qquad (5)$$

Equation 4 depicts the budget constraint on household income where P_g denote price of goods purchased. Thus, P_gG is the income available for purchase of consumption goods, and it depends on the price (P_q) and quantity (Q) of farm output, price (W_x) and quantity (X) of farm inputs, off-farm wages (W) and the amount of time spent working off-farm (M) and exogenous household income such as government transfers, pensions and remittances (A).

Substituting equation 3 into equation 4 yields a farm technology-constrained measure of household income:

$$P_g G = P_q Q\left[X(I_f), F(I_f)^{'}, H, I_f, R\right] - W_x X^{'} + WM^{'} + A \qquad (6)$$

The Kuhn-Tucker first order conditions can be obtained maximising Lagrangean expression ($\mathcal{L}$) over (G, L) and minimising it over (λ, η):

$$\begin{aligned} \mathcal{L} &= U(G, L; H, Z) \\ &+\lambda\left\{P_q Q\left[X(I_f), F(I_f)^{'}, H, I_f, R\right] - W_x X^{'} + WM^{'} + A - P_g G\right\} \\ &+\eta\left[T - F(I_f) - M - L\right] \end{aligned} \qquad (7)$$

where λ and η represent the Lagrange multipliers for the marginal utility of income and time, respectively.

Solving the Kuhn-Tucker conditions, reduced-form expression of the optimal level of household income (Y^*) can be obtained by (Fernandez-Cornejo et al. 2005):

$$Y^* = Y(I_f,\ W_x,\ P_q,\ P_g,\ A,\ H,\ Z,\ R,\ T) \qquad (8)$$

and household demand for consumption goods (G) can be expressed as:

$$G = G(I_f,\ W,\ P_g,\ Y^*,\ H,\ Z,\ T) \qquad (9)$$

Thus, the reduced forms of Y^* and G are influenced by a set of explanatory variables, including I_f. The main aim of this paper is to estimate the effect of I_f on household income, household consumption of goods and other related outcome variables such as food security.

3. Empirical model

As already indicated by the reduced form expression (equation 8), we are interested in estimating the effect of innovation generation activities of farmers on household welfare indicators such as income. A simplified model from linearising this reduced form equation can be expressed as:

$$y = \varphi V + \delta I_f + \mu \qquad (10)$$

where y denotes income or other household well-being indicators such as food security and consumption expenditure. V is a vector of explanatory variables (other than farmer innovation) that influences the outcome variables, and it includes household, farm and contextual characteristics such as age, gender and educational level of household head, household size, farm size, access to credit, asset endowments, social network variables, risk preference and district dummies. I_f is a dummy for farmer innovation and the coefficient δ, measures the effect of farmer innovation on household well-being. This variable is potentially endogenous since innovation is not randomly assigned and farmers may decide whether or not to innovate (i.e. self-selection bias). In other words, innovative farmers may be systematically different from non-innovators and these differences may obscure the true effect of innovation on household well-being. Thus, estimating equation 10 with ordinary least squares (OLS) regression technique may yield biased results.

Commonly suggested methods for addressing such biases include Heckman selection, instrumental variable (IV) and propensity score matching (PSM). Each of these methods, however, has some limitations. For instance, both Heckman selection and IV methods tend to impose a functional form assumption by assuming that farmer innovations have only an intercept shift and not a slope shift in the outcome variables (Alene and Manyong 2007). Though PSM tackles the above problem by avoiding functional form assumptions, it assumes selection is based on observable variables, but there is likely to be unobserved heterogeneity because farmers innate abilities, skills and motivation are likely to influence their innovative behaviour. PSM, therefore, produces bias result when there are unobservable factors that influence both innovative behaviour and the outcome indicators.

In order to address these issues, we use the endogenous switching regression (ESR) technique. This model is increasingly being applied in evaluating the impacts of decisions of farmers on farm performance or household well-being (e.g. Fuglie and Bosch 1995; Di Falco et al. 2011; Kleemann and Abdulai 2013; Negash and Swinnen 2013; Noltze et al. 2013).

In the ESR method, separate outcome equations are specified for each regime, conditional on a selection equation. Thus in our case, we estimate separate household well-being indicators for innovators and non-innovators, conditional on the innovation decision:

$$I_f = \gamma K + \varepsilon \qquad (11)$$
$$y_1 = \varphi_1 V + \mu_1 \quad if\, I_f = 1 \qquad (12)$$
$$y_0 = \varphi_0 V + \mu_0 \quad if\, I_f = 0 \qquad (13)$$

where K is a set of all the explanatory variables already defined in equation 5. y_1 and y_0 represent a vector of welfare indicators for innovators and non-innovators, respectively. φ_1 and φ_0 are parameters to be estimated for the innovators and non-innovators regimes, respectively. When the error term of the selection equation ($\mathcal{E}$) is correlated with the error terms of the outcome equation of innovators (μ_1) and non-innovators (μ_0), then we have a selection bias problem. The error terms $\mathcal{E}$, μ_1 and μ_0 are assumed to have a joint-normal distribution with mean vector 0, and a covariance matrix specified as (Fuglie and Bosch 1995):

$$\operatorname{cov}(\varepsilon, \mu_1, \mu_0) = \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{\mu_1\varepsilon} & \sigma_{\mu_0\varepsilon} \\ \sigma_{\mu_1\varepsilon} & \sigma_{\mu_1}^2 & \sigma_{\mu_1\mu_0} \\ \sigma_{\mu_0\varepsilon} & \sigma_{\mu_1\mu_0} & \sigma_{\mu_0}^2 \end{pmatrix} \qquad (14)$$

where var($\mathcal{E}$)= σ_ε^2, which is assumed to be 1 since γ is only estimable up to a scale factor (Maddala 1983); var (μ_1) = $\sigma_{\mu_1}^2$, var (μ_0)= $\sigma_{\mu_0}^2$, cov (μ_1, $\mathcal{E}$)= $\sigma_{\mu_1\varepsilon}$, cov ($\mu_0$, $\mathcal{E}$)= $\sigma_{\mu_0\varepsilon}$, and cov ($\mu_1$, μ_0)= $\sigma_{\mu_1\mu_0}$. The expected values of the error terms μ_1 *and* μ_0 can be expressed as (Fuglie and Bosch 1995):

$$E(\mu_1 | I_f = 1) = \sigma_{\mu_1\varepsilon}\lambda_1 \qquad (15)$$
$$E(\mu_0 | I_f = 0) = \sigma_{\mu_0\varepsilon}\lambda_0 \qquad (16)$$

where λ_1 and λ_0 are the inverse mills ratios (IMR) evaluated at γK. Equations 12 and 13 can then be specified as (Maddala, 1983):

$$y_1 = \varphi_1 V + \sigma_{\mu_1\varepsilon}\lambda_1 + \xi_1 \quad if\, I_f = 1 \qquad (17)$$
$$y_0 = \varphi_0 V + \sigma_{\mu_0\varepsilon}\lambda_0 + \xi_0 \quad if\, I_f = 0 \qquad (18)$$

Thus, estimates from the selection equation are used to compute λ_1 and λ_0 which are then added to the outcome equations to correct for selection bias, and this can be estimated using a two-stage method (Maddala 1983). However, we use the full information maximum likelihood (FIML) estimation approach (Lokshin and Sajaia 2004) which estimates the selection and outcome equations simultaneously[1]. This is more efficient than the two-step procedure. If $\sigma_{\mu_1\varepsilon}$ and $\sigma_{\mu_0\varepsilon}$ in equations 17 and 18 are statistically significant, we have endogenous switching. Otherwise, we have exogenous switching.

While the FIML ESR model is identified through non-linearities of λ_1 and λ_0 (Lokshin and Sajaia 2004), a better identification requires an exclusion restriction. That is, we need at least one variable that affects farmers' innovation decisions but does not directly affect any of the households' well-being indicators. Taking inspiration from the agricultural innovation literature on the importance of information in farmers' innovation decisions, we use agricultural information constraint as our identification strategy. Information-related variables have been used for identification purposes in some previous studies on impact of agricultural innovations (e.g. Kabunga et al. 2011; Asfaw et al. 2012; Negash and Swinnen 2013). We hypothesise that households that do not face agricultural information constraints are more likely to learn of existing or new practices and processes and consequently experiment and adapt them to their local environments or develop novel applications. However, agricultural information constraint is not directly related to the household well-being[2].

In this study, we are interested in how innovation decisions affect the well-being of farm households. The coefficients from the ESR model can be used to derive the expected values of well-being, which are then used in estimating the unbiased average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU). The ATT compares the well-being of innovators with and without innovation while the ATU compares the well-being of the non-innovators with and without innovation. For an innovative household with characteristics K and V, the expected value of well-being is given as:

$$E(y_1 | I_f = 1) = \varphi_1 V + \sigma_{\mu_1\varepsilon}\lambda_1 \qquad (19)$$

The expected value of well-being of the same household had it chosen not to innovate is:

$$E(y_0 | I_f = 1) = \varphi_0 V + \sigma_{\mu_0\varepsilon}\lambda_1 \qquad (20)$$

Thus, the change in well-being as a result of innovation is:

$$ATT = E(y_1 | I_f = 1) - E(y_0 | I_f = 1) = V(\varphi_1 - \varphi_0) + \lambda_1(\sigma_{\mu_1\varepsilon} - \sigma_{\mu_0\varepsilon}) \qquad (21)$$

[1] The models were estimated using the *movestay* command in Stata.

[2] Following Di Falco et al. (2011), the admissibility of the information constraint variable as a valid instrument is established by performing a falsification test: if a variable is an appropriate selection instrument, it will affect innovation decision but it will not affect the welfare outcomes of non-innovating households. We found that the information constraint variable satisfy these conditions.

Similarly, the expected value of well-being of non-innovators without innovation and the expected value of well-being of non-innovators had they decided to innovate are, respectively:

$$E(y_0 \left| I_f = 0\right.) = \varphi_0 V + \sigma_{\mu_0 \varepsilon} \lambda_0 \qquad (22)$$

$$E(y_1 \left| I_f = 0\right.) = \varphi_1 V + \sigma_{\mu_1 \varepsilon} \lambda_0 \qquad (23)$$

Hence, the change in well-being for non-innovators had they innovated is:

$$ATU = E(y_1 \left| I_f = 0\right.) - E(y_0 \left| I_f = 0\right.) = V(\varphi_1 - \varphi_0) + \lambda_0 (\sigma_{\mu_1 \varepsilon} - \sigma_{\mu_0 \varepsilon}) \qquad (24)$$

4. Choice of outcome measures

Farmers implement various innovations within their farming systems which may contribute to household welfare. We evaluate the effect of these innovations on a number of welfare outcomes, such as farm and household income, consumption expenditure and food security. Below, we explain these outcome measures in detail.

4.1 Farm and household income

Most of the innovation practices of farm households are yield-related, hence, are expected to affect productivity and consequently farm income. We therefore measure the effect of innovation on farm income. However, farmer innovation may result in resource reallocation which could have indirect effect on household income. For instance, a household involved in labour-saving innovations could have surplus labour for non-farm activities and earn extra income. To capture these potential indirect effects, we also analyse the effect of farmer innovation on total household income, which comprises farm and off-farm income. Gross farm income consists of revenue from sale of crops, livestock and livestock products as well as home consumption of farm produce valued at local market prices. All production costs (e.g. seed, fertilizer, pesticide, hired labour, animal feed, veterinary, etc.) incurred by households 12-month prior to the survey were then deducted from the gross farm income to derive the farm income. Off-farm income includes wages and salaries from agricultural and non-agricultural activities, profits from off-farm self-employment, pensions, remittances, rental income, and income from other off-farm sources. The farm and total household income were expressed in annual per adult equivalent[3] (AE) basis.

4.2 Household consumption expenditure

While household income can be used as a measure of household well-being, consumption expenditure is often preferred because it is less prone to seasonal fluctuations and

[3] We use the OECD adult equivalent scale which is given by: $1+0.7(A-1)+0.5C$, where A and C represent the number of adults and children in a household, respectively.

measurement errors, hence, more reliable (Deaton 1997). We therefore took advantage of our two survey rounds to obtain household consumption data in the second period. It is expected that innovative practices of households result in increased yields or outputs, thus, more consumption of farm products or more income from sales of products for the consumption of other goods. Also, the resource allocation effects of innovation may also induce changes in consumption expenditure.

The consumption expenditure consists of different sub-components including food consumption, housing, energy, transportation, communication, health, and educational expenses, expenditures on other consumer durables and non-durables and transfer payments made by households. The survey questionnaire captured the value of household consumption out of purchases, home production and, all items received in kind. The non-purchased goods were valued at local market prices. A 7-day recall period was used to capture food expenditure, and a 30-day recall period was used for frequently purchased items or services and non-durable goods; while a 12-month recall period was used for durable items and transfer payments. All the recall periods were standardised to one year, and the different sub-components were aggregated to obtain total household consumption expenditure, which was expressed in per AE terms.

4.3 Food and nutrition security

There is no unified measure of food and nutrition security, and this is partly due to its complexity and multidimensionality (Pinstrup-Andersen 2009; Barrett 2010). Many studies have used different measures ranging from caloric intake, dietary quality, and anthropometric estimates in order to capture the key dimensions of food security: availability, accessibility, utilization and stability. Most these measures are, however, relatively time-consuming and costly to implement (de Haen et al. 2011). In this study we employ the standard food security measure − food consumption expenditure, as well as three other indicators which are relatively quick and easy to measure. These are food gap/deficit, Household Hunger Scale (HHS) and Household Dietary Diversity Score (HDDS).

The food consumption expenditure forms part of the total household consumption expenditure discussed above. Farmer innovation is expected to affect household food consumption since most inhabitants in the study area are subsistence farmers. The food gap/deficit is a subjective measure of food security, and it refers to the number of months in the past 12 months that households have difficulty satisfying their food needs due to depletion of own food stocks or lack of money to purchase food. This measure is also known as the months of inadequate household food provisioning (MIHFP) (Bilinsky and Swindale 2005). Farming in the study region is mainly rain-fed and rainfall is highly erratic. This results in pervasive seasonal food insecurity so smoothing food consumption throughout the year is a huge challenge for most households.

Another perception-based measure of food insecurity we employed is the HHS, which is most suitable to use in highly food insecure areas (Ballard et al. 2011), as in our case. The HHS is a subset of the Household Food Insecurity Access Scale (HFIAS) developed by Food and Nutrition Technical Assistance (FANTA) project of the US-AID, but unlike the HFIAS, the HHS has been validated for cross-cultural use (Ballard et al. 2011). The HHS is related to food access dimension of food security, and it is based on three questions. That is, how often in the past 30 days: 1) was there no food of any kind in the house; 2) did a household member go to sleep hungry; and 3) did a household member go a whole day without eating. The response to each question was coded: 0=never; 1=rarely or sometimes[4]; and 2=often. The sum of these responses yields the HHS score, which ranges from 0 (no hunger) to 6 (severe hunger). Households were interviewed in April 2012 which is around the peak period of the lean season in the study area; hence, an appropriate period to use the HHS, which measures severe level of food insecurity.

Finally, we use a dietary diversity indicator, the HDDS as another measure of the access facet of food and nutrition security. We assess whether the potential improvement in food production or household income though innovation translates into better nutritional quality of diets. The HDDS, which was also developed by the FANTA project, is obtained by simply summing the total number of 12 food groups consumed by household members in the home during the past 24 hours (Swindale and Bilinsky 2006). The food groups include cereal, roots and tubers, legumes and nuts, vegetables, fruits, fish and seafood, eggs, meat and poultry, milk and milk products, oils and fats, sweets, and miscellaneous such as spices[5]. As suggested by Swindale and Bilinsky (2006), we made sure that there were no special occasions such as funeral in the past 24 hours within the sample households which might influence their food consumption pattern.

5. Data and Sample Characteristics

The empirical analysis is based on data for the 2011-2012 agricultural season obtained from a household survey conducted within the research programme—West African Science Service Center for Climate Change and Adapted Land Use (WASCAL) funded by the German Federal Ministry of Education and Research (BMBF). Data collection took place in Bongo, Kassena Nankana East and Kassena Nankana West districts in Upper East Region, one of the poorest administrative regions of Ghana. Part of this research aimed at examining the effect of a participatory extension approach, the Farmer Field Fora (FFF) on farmers' innovativeness; hence, this influenced the sampling strategy used in this study. Descriptions of the study area and the sampling design are presented in paper one of this thesis. Overall, our sample consists of 409 farm households (101, 156 and 152 from Bongo, Kassena

[4] For data collection, "rarely" and "sometimes'' categories were separated as recommended by Ballard et al. (2011).

[5] We use a disaggregated set of food groups which were then combined into 12 food groups to generate the HDDS (Swindale and Bilinsky 2006).

Nankana East and Kassena Nankana West districts, respectively) randomly selected from the three districts.

Data collection was conducted by experienced enumerators who were highly trained for this research. Interviews were conducted with the aid of pre-tested questionnaires and were supervised by the author. Due to the bulky nature the questionnaire and the potential differences in perceived food insecurity across the three districts as a result of different survey days, the data collection took place in two phases. The first phase was conducted between December 2012 and March 2013. The questionnaire used in this phase captured data on household and plot characteristics, crop and livestock production, off-farm income earning activities, innovation generation activities, access to infrastructural services, information and social interventions, household experiences with shocks, climate change adaptation strategies and risk preferences[6]. The second wave of the survey took place just after the end of the first phase and was conducted simultaneously in the three districts so that the households' subjective responses to food insecurity are not influenced by differences in survey days. In the second phase, the same households were revisited and all but one household were re-interviewed. Thus, the sample size in the second phase is 408. The second phase was used to obtain data on the food security indicators (HHS, HDDS and food consumption) as well as household consumption expenditure.

Table 1 outlines the description of the variables used in the regression and their mean values. The explanatory variables were motivated by literature on agricultural innovation adoption, and they include household and farm characteristics (e.g. age, gender and education of the household head; household size, dependency ratio, farm size and risk attitude) as well as institutional and access related variables (e.g. access to credit, information, and motorable roads and FFF participation). We also include district dummies to control for district fixed effects. The table shows that an average household has 7 people with high dependency ratio. Majority of the households are male-headed, and household heads are mostly middle-aged with very low level of education. Households generally have about 5 acres of land and largely experience shocks, particularly climatic shocks. Majority of the households are credit constrained, and about half of them also face agricultural information constraints.

[6] We measured households' subjective risk preferences using the Ordered Lottery Selection Design with real payoffs (Harrison and Rutström 2008).

Table 1: Definition of variables in the regression

Variable	Description	Mean	SD
Treatment variable			
Innovation	Household implemented innovation practices in the past 12 months	0.42	0.41
Explanatory variables			
Age	Age of household head	49.42	14.88
Gender	Gender of household head (1=male)	0.86	0.35
Household size	Number of household members	6.64	2.59
Dependency ratio	Ratio of members aged below 15 and above 64 to those aged 15-64	0.89	0.79
Education	Education of household head (years)	1.67	1.10
FFF participation	Household member participated in Farmer Field Fora (FFF)	0.45	0.50
Land holding	Total land owned by household in acres	4.56	4.15
Livestock holding	Total livestock holding of household in Tropical Livestock Units (TLU)	2.92	3.41
Assets value	Total value of non-land productive assets in 100 GH¢[a]	4.54	6.92
Off-farm activity	Household engage in off-farm income earning activities	0.76	0.43
Credit access	Household has access to credit	0.26	0.43
Road distance	Distance to nearest all-weather road in km	0.54	0.84
Group membership	A household member belongs to a group	0.64	0.48
Climate shock	Household suffered from droughts or floods in the past 5 years	0.91	0.29
Pest and disease shock	Household farm affected by pests or diseases in the past 5 years	0.82	0.39
Labour shock	Death or illness of a household member one year prior to survey	0.60	0.49
Risk averse	Household is risk averse	0.40	0.49
Information constrained	Household faces agricultural information constraints	0.49	0.50
Bongo District	Household is located in Bongo District	0.25	0.43
KNW District	Household is located in Kassena Nankana West District	0.37	0.48
KNE District	Household is located in Kassena Nankana East District	0.38	0.49
Outcome variables			
Farm income	Total farm income per adult equivalent	317.57	448.42
Household income	Total household income per adult equivalent	531.69	768.68
Consumption expenditure	Total household consumption expenditure per adult equivalent	779.08	627.29
Food consumption	Total food consumption expenditure per adult equivalent	453.83	330.66
Food gap/deficit	Number of months of inadequate household food provisioning	2.85	1.68
HHS	Household Hunger Scale Score	1.13	1.27
HDDS	Household Dietary Diversity Score	7.14	1.96

[a] The exchange rate at the time of the survey was 1 euro = 2.5 GH¢

The summary statistics of the outcome variables, which are presented in the lower part of Table 1, indicate that the average farm income per AE is almost 318GH¢, and this contributes about 60 percent to total household income per AE. Similarly, the average food consumption expenditure of nearly 454GH¢ accounts for about 58 percent of average total consumption expenditure. On average, households experience about 3 months (April to June) of inadequate food provisioning. The average HHS of about 1.13 suggests that severe food insecurity or hunger is not pervasive in the study region. The table also shows that about 42 percent of the sampled households implemented at least one innovation generation activity in the past 12 months, and this is our treatment variable. Table 2 shows the different domains in which the farmers innovated.

Table 2: Domains of innovations implemented by farm households

Domain	Proportion of households (%)
Crops and crop varieties	51.19
Method of planting	19.64
Soil fertility	17.26
Animal Husbandry	12.50
Weed control	7.74
Land preparation	7.14
Cropping pattern	6.55
Pests and Diseases control	5.95
Storage	4.17
Agroforestry	4.17
Farm tool/equipment	1.19
Soil and Water Conservation	1.19
Others	1.79

Most of the farmer innovations involved informal experimentation or minor modification of common or external practices. There were also few innovations which were major modification of current practices or even completely novel. Majority of the innovations are related to crop varieties and agronomic practices, as shown in Table 3. The main domain is related to crops and crop varieties, and this consists of the introduction of new crops or crop varieties into a community and informal experimentation of different variety of crops to select best ones that suit a farming system. The important agronomic innovations include new or modification of land preparation and planting methods as well as cropping pattern (e.g. new methods of intercropping or planting with reduced seed rate); soil fertility measures such as new methods of compost preparation or preventing soil nutrient loss; weeds, pest and diseases control methods such as use of plant extracts. Some of the innovations are related to livestock production, and it includes new formulations of animal feed and new herbal remedies in the treatment of livestock diseases (ethnovertinary practices). Other minor domains of the farmers' innovations are related to storage, farm tool, agroforestry and soil and water conservation.

Table 3 presents descriptive statistics of the variables in the regression, disaggregated by innovation status. There are remarkable differences between innovators and non-innovators with respect to some of the household characteristics and well-being indicators. The heads of innovative households appear to be significantly younger and more educated than non-innovators. Innovative households also tend to be less risk averse and less agricultural information constrained but likely to own more land. There are also significant differences in terms of FFF participation and group membership between the two groups, and the KNW District appear to have significantly higher number of innovative farmers. As expected, innovative households have significantly higher farm income which further results in significantly higher total household income. They also seem to have fewer days of insufficient food. Average consumption expenditure is slightly higher for innovative households but the difference in means is not statistically significant.

Table 3: Descriptive statistics of variables in the regression

	Innovators		Non-innovators		
Variable	Mean	SD	Mean	SD	t-Stat[a]
Explanatory variables					
Age	46.80	14.22	51.63	15.59	-3.19***
Gender	0.86	0.35	0.85	0.36	0.30
Household size	6.57	2.20	6.65	2.84	-0.31
Dependency ratio	0.87	0.75	0.90	0.81	-0.38
Education	3.31	4.37	2.04	3.88	3.09***
FFF participation	0.54	0.50	0.39	0.49	3.06***
Land holding	5.20	5.60	4.11	3.37	2.47**
Livestock holding	3.04	3.47	2.79	3.41	0.74
Assets value	5.33	6.80	3.97	7.28	1.92*
Off-farm activity	0.80	0.40	0.73	0.45	1.66*
Credit access	0.29	0.46	0.22	0.42	1.55
Road distance	0.54	0.89	0.55	0.87	-0.01
Group membership	0.74	0.44	0.57	0.50	3.69***
Climate shock	0.88	0.32	0.93	0.26	-1.68*
Pest and disease shock	0.84	0.37	0.81	0.39	0.78
Labour shock	0.58	0.50	0.61	0.49	-0.66
Risk averse	0.34	0.47	0.44	0.50	-2.13**
Information constrained	0.36	0.48	0.59	0.49	-4.64***
Bongo District	0.21	0.41	0.27	0.45	-1.51
KNW District	0.44	0.50	0.32	0.47	2.42**
KNE District	0.35	0.48	0.40	0.49	-1.05
Outcome variables					
Farm income	399.88	538.64	259.96	362.77	3.14***
Household income	624.81	761.69	466.51	768.41	2.06**
Consumption expenditure	827.00	624.71	745.88	628.22	1.29
Food consumption	478.10	376.01	437.02	294.84	1.23
Food gap/deficit	2.62	1.53	3.00	1.76	-2.30**
HHS	1.02	1.10	1.21	1.37	-1.47
HDDS	7.30	1.97	7.02	1.94	1.40

[a] test of mean difference between innovators and non-innovators characteristics.
***, **, * represent 1%, 5%, and 10% significance level, respectively

6. Impact of farmer innovation

In this section, we present the results of the effect of farmer innovation on several household well-being indicators. We first look at the outcomes of innovation practices as subjectively stated by the innovative farmers before presenting the econometric results.

6.1 Subjective outcome of farmer innovation

To corroborate the results from the regression analysis, all innovative farmers were asked about the outcomes observed from their innovation practices, and their subjective responses are summarised in Figure 1. The figure shows that increased productivity is the major outcome of most of the farmers' innovations. Most of the innovative practices listed by the farmers are yield-related (e.g. crop and crop varieties, soil fertility and pest and disease control); so, it is not surprising that increased production is the most mentioned outcome. Increased income and food security are also important outcomes stated by the farmers. These two outcomes are also related to increased production and together, they point out the potential positive well-being effects of farmer innovation. Another positive effect stated by the farmers is labour saving, thus, reduction in production costs and freeing labour for off-farm employment. Most often, farmers implement informal experiments in order make better farming decisions, while others discover innovations out of curiosity or serendipity; hence, this explains the significant number of innovators asserting increased knowledge or satisfaction as outcomes of their innovations. A few of the farmers indicated that their innovations were unsuccessful, and this is expected since innovation generally involves decision making under uncertainty which can result in positive or negative outcomes. Similar subjective outcomes were obtained by Kummer (2011) and Leitgeb et al. (2013) in studies on farmer experimenters in Austria and Cuba, respectively.

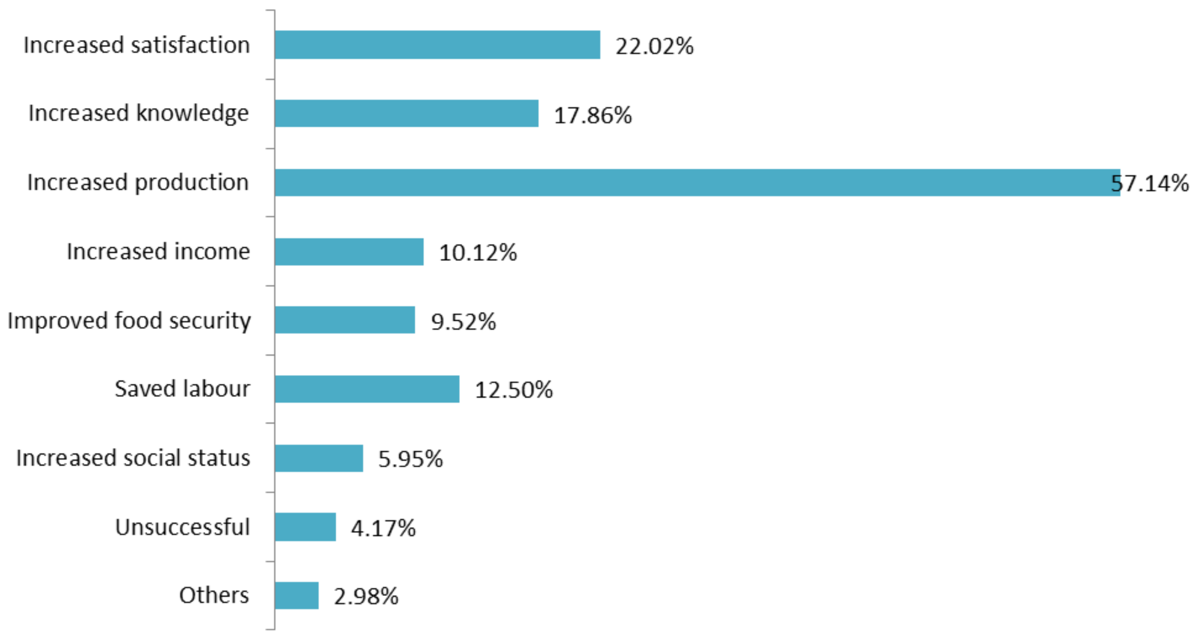

Figure 1: Subjective outcome of farmer innovation

6.2 Econometric results

The descriptive analysis in the previous section revealed significant differences in some of the well-being indicators between innovators and non-innovators. Also, the farmers' perception shows potential positive effects of farmer innovation. To properly analyse the impacts of farmer innovation, we use an econometric technique, the FIML ESR. The FIML ESR model involves a selection equation and separate outcome equations for innovators and non-innovators which are estimated simultaneously. The selection equation is about the determinants of innovation decision, and the results are shown in Table A1 in the appendix. Our exclusion restriction variable, agricultural information constraint is statistically significant in all the models, thus satisfying the instrument relevance condition. The negative coefficient confirms our expectation that information-constrained households are less likely to innovate[7]. We now look at the results for each of the outcome indicators.

6.2.1 Farm and household income effects

The second-stage estimates of the FIML ESR models for the farm and household income equations are presented in Table 4. The table shows how each of the explanatory variables affects the two income measures. ρ_1 and ρ_0, the correlation coefficients between the error terms of the selection and outcome equations reported at the bottom part of the table, provide an indication of selection bias. A statistical significance of any of them suggests that self-selection would be an issue if not accounted for. In all the two income models in Table 4, the correlation coefficients for the innovators (ρ_1) and non-innovators (ρ_0) equations are both negative but only the ρ_1 coefficients are statistically significant, suggesting that there is self-selection among innovators. Thus, farm households with lower than average farm and household income are more likely to innovate, while the non-innovators are not better or worse off than a random farm household. The significance of the likelihood ratio tests for independence of equations also indicates that there is joint dependence between the selection equations and the income equations for innovators and non-innovators.

The estimation results show that household size and livestock holding significantly affect the farm income of both innovators and non-innovators. An increase in household size results in a decline in farm income while large livestock holding contributes positively to farm income. There are differences between what determines farm income among innovators and non-innovators. For example, gender of household head, credit access and risk aversion are significantly associated with the farm income of innovators, but the effects are insignificant among non-innovators. Conversely, FFF participation, land holding and labour shock influence the farm income of only non-innovators. The fact that land holding and labour shock are only significant in the case of non-innovators suggests that innovators may be implementing input saving innovations. The results for the household income model also indicate similar differences in the significance of the coefficients between the innovators

[7] The first-stage results on the determinants of farmer innovation are not discussed in this paper since a detailed analysis and discussion were presented in chapter one of this thesis.

and non-innovators equations. However, there are notable differences across the two income models. For instance, the value of household assets, off-farm job and district dummies positively and significantly influence household income but not farm income. Thus, factors which significantly affect farm income may not necessarily influence household income, and this is expected since most of the households (76%) earn income from non-farm activities to supplement household income.

Table 4: ESR results for farm and household income

	Farm income per AE (log)		Household income per AE (log)	
	Innovators	Non-innovators	Innovators	Non-innovators
Age	0.004 (0.008)	0.003 (0.005)	-0.000 (0.006)	0.007 (0.004)*
Gender	0.790 (0.313)**	0.163 (0.219)	0.463 (0.234)**	0.209 (0.173)
Household size	-0.097 (0.049)**	-0.155 (0.030) ***	-0.111 (0.038)***	-0.134 (0.024) ***
Dependency ratio	-0.124 (0.141)	-0.072 (0.087)	-0.167 (0.105)	-0.121 (0.072)*
Education	-0.023 (0.030)	-0.010 (0.021)	-0.030 (0.022)	0.009 (0.017)
FFF participation[8]	0.236 (0.465)	0.682 (0.325)**	-0.059 (0.345)	0.432 (0.267)
Land holding	0.014 (0.029)	0.124 (0.026)***	-0.007 (0.018)	0.075 (0.021)***
Livestock holding	0.138 (0.037)***	0.065 (0.025)***	0.133 (0.027) ***	0.057 (0.021)***
Assets value	0.003 (0.017)	0.018 (0.014)	0.000 (0.000)**	0.000 (0.000)***
Off-farm activity	0.113 (0.262)	-0.130 (0.171)	0.640 (0.198) ***	0.395 (0.137)***
Credit access	-0.419 (0.234)*	0.249 (0.174)	-0.097 (0.174)	0.240 (0.140)*
Group membership	-0.045 (0.279)	-0.217 (0.195)	0.049 (0.211)	-0.025 (0.153)
Climate shock	-0.107 (0.348)	-0.152 (0.289)	-0.111 (0.252)	-0.208 (0.251)
Pest and disease shock	-0.218 (0.292)	0.182 (0.188)	-0.306 (0.220)	0.076 (0.154)
Labour shock	-0.161 (0.219)	-0.350 (0.155)**	-0.144 (0.163)	-0.341 (0.128)***
Risk averse	0.481 (0.220)**	0.022 (0.155)	0.014 (0.167)	0.079 (0.122)
KNW District	0.415 (0.327)	0.157 (0.224)	0.694 (0.240) ***	0.108 (0.179)
KNE District	0.527 (0.344)	0.354 (0.216)	0.860 (0.245) ***	0.427 (0.176)**
Constant	5.859 (0.815)***	4.763 (0.601)***	6.039 (0.630) ***	4.757 (0.518) ***
$ln\sigma_1, ln\sigma_0$	0.442 (0.083)***	0.027 (0.063)	0.094 (0.103)	-0.145 (0.065)**
ρ_1, ρ_0	-0.981 (0.016)***	-0.263 (0.266)	-0.848 (0.076) ***	-0.301 (0.267)
LR test of indep. eqns.		78.17***		19.79***
Number of observations		409		409
Log likelihood		-742.738		-733.634

***, **, * represent 1%, 5%, and 10% significance level, respectively

The estimates of the treatment effects of farmer innovation on farm and household income are presented in Table 8. The predicted farm and household income per AE from the ESR models are used to compute both the ATT and ATU. The ATT measures the difference between the mean income of innovators and what they would have earned if they had not innovated, while the ATU indicates the difference between the mean income of non-innovators and what they would have obtained if they had innovated. The results show that farmer innovation has a positive and significant effect on both farm and household income

[8] In all the models, we use the predicted probability of FFF participation since FFF participation is potentially endogenous.

of the innovating households. Innovation increases farm and household income per AE of innovators by about 11 percent and 9 percent respectively, and this is statistically significant. The positive and significance of the ATU estimates suggests that households that did not innovate would have realised an even higher income benefits had they innovated. Specifically, if farm households that did not innovate had innovated, they would have increased their farm and household income per AE by 51 percent and 28 percent, respectively. Overall, both innovators and non-innovators would derive income benefits from innovation, confirming the farmers' subjective reports of increased productivity and income effects of their innovations. These findings also support the results of numerous studies (e.g. Amare et al. 2012; Noltze et al. 2013) on the significant contribution of agricultural innovations to household income.

6.2.2 Consumption expenditure effects

Table 5 shows the estimation results of the consumption expenditure per AE model. The results show that household size and dependency ratio significantly reduce consumption expenditure of both innovators and non-innovators, but the effect is more pronounced for innovators. The value of household assets also significantly increases consumption expenditure for both groups, but the coefficients for other wealth-related variables (e.g. livestock holding, off-farm activity) are not statistically significant. The positive and significant coefficient of the district dummies in both innovation regimes suggest that farm households in the KNE and KNW districts have higher consumption expenditure than those in Bongo district. This is expected since Bongo district is recognised as one of the poorest district in the Upper East region of Ghana (Akudugu and Laube 2013). The results also show some differences between innovators and non-innovators with respect to some of the variables. For instance, climate shock has a negative and significant effect on the expenditure of innovative households, but the effect is positive and insignificant for non-innovators. The statistical significance of the correlation coefficient (ρ_1) suggests that there is selection effect; hence, unobserved factors affect both the innovation decision and household consumption expenditure. In particular, there is positive selection bias but only for innovators as ρ_1 is positive and significant while ρ_0 is not statistically significant. Thus, farm households who choose to innovate have above average consumption expenditure per AE, while those who choose not to innovate are not better or worse off than a random farm household.

We now look at the results for the treatment effect of farmer innovation on consumption expenditure per AE presented in Table 8. The ATT result shows that farm households who innovated increased their consumption expenditure per AE by about 5 percent as a result of their innovations, and the effect is statistically significant. This positive consumption effect may stem from the revenue increase or production cost reduction potential of farmer innovations. This also implies that the positive income effects of farmer innovation reported earlier translate into increased household consumption. The small magnitude of the ATT, however, suggests that households have other important sources of consumption. The ATU result indicates that if non-innovators were to innovate, their consumption expenditure per AE would have declined by 13 percent. This also implies that non-innovating households may have better alternative means of meeting their consumption demands, and their decision not to innovate appear to be rational, at least in terms of consumption expenditure.

Table 5: ESR results for consumption expenditure per AE (log)

	Innovators		Non-innovators	
	Coefficient	SE	Coefficient	SE
Age	-0.001	(0.003)	-0.001	(0.002)
Gender	0.086	(0.118)	0.083	(0.084)
Household size	-0.147***	(0.019)	-0.098***	(0.012)
Dependency ratio	-0.168**	(0.054)	-0.072*	(0.036)
Education	0.027*	(0.011)	-0.001	(0.010)
FFF participation	0.042	(0.171)	0.215	(0.144)
Land holding	0.012	(0.009)	0.010	(0.011)
Livestock holding	-0.005	(0.014)	0.007	(0.011)
Assets value	0.014*	(0.006)	0.014**	(0.004)
Off-farm activity	0.004	(0.098)	0.017	(0.067)
Credit access	-0.119	(0.088)	-0.007	(0.072)
Road distance	0.098*	(0.048)	-0.005	(0.037)
Group membership	0.272*	(0.109)	-0.007	(0.082)
Climate shock	-0.386**	(0.135)	0.171	(0.121)
Pest and disease shock	0.262*	(0.109)	0.002	(0.082)
Labour shock	-0.145	(0.081)	-0.021	(0.063)
Risk averse	-0.157	(0.082)	-0.027	(0.067)
KNW District	0.393**	(0.121)	0.353***	(0.088)
KNE District	0.432***	(0.127)	0.494***	(0.099)
Constant	6.648***	(0.319)	6.335***	(0.289)
$ln\sigma_1, ln\sigma_0$	-0.564***	(0.115)	-0.821***	(0.129)
ρ_1, ρ_0	0.911***	(0.063)	-0.412	(0.499)
LR test of indep. eqns.			8.14***	
Number of observations			408	
Log likelihood			-458.21	

***, **, * represent 1%, 5%, and 10% significance level, respectively

6.2.3 Food and nutrition security effects

As already indicated, four different measures of food security are used in estimating the effect of farmer innovation on food security. The second stage results for all the four indicators are presented in Tables 6 and 7. The results of the correlation coefficients (ρ_1 and ρ_0) indicate the absence of selection bias in the HHS and HDDS models, implying that unobserved factors do not substantially affect both the innovation decision and these two food security measures. Conversely, ρ_1 and ρ_0 of the food gap and food consumption expenditure models are not statistically significant, suggesting heterogeneous results depending on the food security indicator employed. The estimated coefficients of the determinants of the four food security measures further highlight the presence of heterogeneous sample and effects. For instance, the included covariates largely influence the various food security indicators differently. Similarly, the variables that explain food security of innovators do not affect that of non-innovators, and vice versa. Only the location variables are statistically significant in all the four models. Similar to the results in the consumption expenditure model, the coefficient of the district dummies suggests that households located in KNE and KNW districts are more food secure compared with households in the relatively poor Bongo district. Among the key determinants of household food security are gender, dependency ratio, value of household assets, pest and disease shock, labour shock and risk attitude.

Table 6: ESR results for food gap and household hunger scale

	Food gap /deficit		Household Hunger Scale (HHS)	
	Innovators	Non-innovators	Innovators	Non-innovators
Age	0.002 (0.013)	-0.006 (0.008)	-0.001 (0.007)	0.003 (0.006)
Gender	-0.255 (0.450)	-0.950 (0.299)***	0.061 (0.259)	-0.445 (0.240)*
Household size	-0.003 (0.072)	0.021 (0.043)	0.048 (0.042)	0.007 (0.035)
Dependency ratio	0.278 (0.206)	0.174 (0.128)	-0.043 (0.114)	0.238 (0.103)**
Education	0.023 (0.043)	-0.017 (0.032)	0.000 (0.026)	0.005 (0.026)
FFF participation	-0.326 (0.667)	0.166 (0.485)	-0.445 (0.396)	-0.419 (0.389)
Land holding	0.056 (0.042)	-0.056 (0.039)	-0.001 (0.022)	-0.031 (0.032)
Livestock holding	-0.101 (0.064)	0.041 (0.037)	-0.021 (0.030)	0.051 (0.030)*
Assets value	0.008 (0.026)	-0.037 (0.016)**	-0.025 (0.013)*	-0.011 (0.013)
Off-farm activity	0.181 (0.377)	-0.139 (0.243)	0.183 (0.214)	-0.266 (0.196)
Credit access	0.039 (0.372)	-0.067 (0.253)	-0.017 (0.185)	0.117 (0.206)
Group membership	0.431 (0.469)	0.118 (0.265)	-0.219 (0.258)	0.132 (0.232)
Climate shock	-0.811 (0.555)	-0.132 (0.421)	-0.215 (0.285)	-1.085 (0.372)***
Pest and disease shock	0.624 (0.447)	0.263 (0.271)	-0.577 (0.252)**	0.456 (0.226)**
Labour shock	-0.214 (0.319)	0.006 (0.226)	0.080 (0.177)	-0.374 (0.184)**
Risk averse	-0.082 (0.334)	0.265 (0.215)		
KNW District	0.102 (0.500)	-0.738 (0.317)**	-0.395 (0.254)	-0.032 (0.256)
KNE District	-0.515 (0.483)	-1.485 (0.312)***	-0.493 (0.278)*	-0.595 (0.257)**
Constant	0.675 (1.251)	5.050 (0.874)***	2.192 (0.797)***	2.686 (0.767)***
$ln\sigma_1, ln\sigma_0$	0.834 (0.194)***	0.456 (0.072)***	0.012 (0.058)	0.233 (0.059)***
ρ_1, ρ_0	0.961 (0.077)***	0.361 (0.256)	-0.050 (0.560)	0.168 (0.405)
LR test of indep. eqns.		7.28***		1.94
Number of observations		409		408
Log likelihood		-989.31		-885.54

***, **, * represent 1%, 5%, and 10% significance level, respectively

The results indicate that female-headed households are more likely to have extra months of food inadequacy and their household members are more likely to experience hunger, but the coefficients are only significant for non-innovators. This is probably due to the fact that women in the study region have limited access to land and other resources needed to achieve food security (Apusigah 2009). This is also in line with studies that found that female-headed households are more likely to be food insecure than male-headed households (Kassie et al. 2014). The value of household assets significantly reduces hunger and increases food consumption among innovators, while it significantly decreases the number of months of food shortages for non-innovators. This is plausible since households in the study region have a tendency of depleting their productive assets as a coping mechanism to food insecurity (Quaye 2008). Pest and disease shocks significantly affect the hunger status of households, but surprisingly, the effect is negative for innovators. Labour shock also negatively and significantly reduces household food consumption and dietary diversity, but only for the innovators. Similarly, innovative but risk averse households are more likely realise a decrease in both food consumption expenditure and dietary diversity.

Table 7: ESR results for food consumption expenditure and household dietary diversity

	Food consumption expenditure per AE (log)		Household Dietary Diversity Score (HDDS)	
	Innovators	Non-innovators	Innovators	Non-innovators
Age	-0.001 (0.003)	0.000 (0.002)	-0.024 (0.011)**	0.003 (0.008)
Gender	0.061 (0.115)	0.095 (0.087)	0.227 (0.403)	0.355 (0.313)
Household size	-0.147 (0.019)***	-0.102 (0.012)***	0.046 (0.065)	-0.041 (0.044)
Dependency ratio	-0.133 (0.054)**	-0.030 (0.037)	-0.007 (0.179)	-0.105 (0.131)
Education	0.013 (0.011)	-0.003 (0.010)	0.000 (0.039)	-0.006 (0.035)
FFF participation	0.169 (0.167)	0.225 (0.146)	-1.226 (0.596)**	0.818 (0.505)
Land holding	0.009 (0.009)	0.004 (0.011)	0.043 (0.030)	0.075 (0.042)*
Livestock holding	-0.011 (0.013)	0.000 (0.011)	0.026 (0.046)	0.043(0.039)
Assets value	0.012 (0.006)**	0.004 (0.005)	0.025 (0.021)	0.026(0.016)
Off-farm activity	0.004 (0.098)	0.016 (0.070)	-0.261 (0.336)	1.052 (0.248)***
Credit access	-0.033 (0.085)	0.013 (0.074)	-0.462 (0.292)	-0.008 (0.262)
Road distance	0.031 (0.045)	-0.006 (0.039)	-0.143 (0.153)	0.050 (0.140)
Group membership	0.182 (0.110)*	-0.029 (0.081)	0.587 (0.379)	-0.068 (0.304)
Climate shock	-0.357 (0.130)***	0.145 (0.126)	0.051 (0.425)	-0.767 (0.490)
Pest and disease shock	0.265 (0.107)**	-0.052 (0.083)	0.022 (0.382)	0.187 (0.295)
Labour shock	-0.151 (0.079)*	-0.014 (0.066)	-0.707 (0.276)**	-0.299 (0.232)
Risk averse	-0.199 (0.081)**	-0.014 (0.066)	-0.496 (0.295)*	0.189 (0.242)
KNW District	0.485 (0.118)***	0.433 (0.091)***	2.465 (0.403)***	1.371 (0.326)***
KNE District	0.446 (0.123)***	0.510 (0.097)***	2.542 (0.428)***	1.605 (0.331)***
Constant	6.227 (0.316)***	5.875 (0.275)***	6.118 (1.158)***	5.169 (1.075)***
$ln\sigma_1, ln\sigma_0$	-0.636 (0.132)***	-0.782 (0.106)***	0.489 (0.096)***	0.471 (0.083)***
ρ_1, ρ_0	0.819 (0.120)***	-0.435 (0.370)	0.375 (0.298)	0.268 (0.479)
LR test of indep. eqns.		4.04***		3.55*
Number of observations		408		408
Log likelihood		-473.00		-1009.12

***, **, * represent 1%, 5%, and 10% significance level, respectively

The results for treatment effects of farmer innovation on food security are presented in Table 8. The results indicate that farmer innovations play a key role in food insecurity reduction among innovators. The innovations of farm households help to reduce the length of food gap periods by one month. In other words, if households that innovated were not to innovate, they would have had an extra month of food insufficiency. Analogously, farmer innovation significantly reduces household hunger by 0.50 index points, and this amounts to about 33 percent reduction in the severe level of food insecurity for innovators. In addition, the innovations significantly caused an increase in food consumption expenditure per AE by about 5 percent for innovative households, which further confirms the positive food security effects of farmer innovation. The ATT estimate for the HDDS, however, suggests that farmer innovation does not increase household dietary diversity. Specifically, innovations significantly decrease dietary diversity by about 9 percent for innovators. This suggests that the high productivity and income benefits of farmer innovation do not necessarily translate into nutritious diets. Thus, the increased food consumption expenditure reported earlier is related to availability, and not diversity of food. In fact, the data on household expenditure indicates that a large share of the expenditure on food is devoted to cereal staples such as millet, maize and sorghum. Overall, farmer innovation improves food security for innovative households, and this corroborates the subjective outcomes reported by the innovators as well as anecdotal or qualitative evidences on the impact of farmer innovation (e.g. Reij and Waters-Bayer 2001; Sawadogo et al. 2001; Reij et al. 2009; Avornyo et al. 2011).

The ATU results show heterogeneous food security effects of farmer innovation for non-innovators if they were to innovate. For instance, non-innovators would have reduced the number of months of household food inadequacy substantially if they were to innovate. However, in terms of dietary diversity and food consumption expenditure, they are better off not innovating since it appears that their food consumption and dietary diversity would have declined significantly had they decided to innovate. A similar heterogeneous food security result was obtained by Negash and Swinnen (2013), but their study was based on crop technology adoption.

Table 8: Treatment effects of farmer innovation

Sample	Innovation decision		Treatment effect	Treatment effect in %
	Innovating	Not innovating		
Farm income per AE (log)				
Innovators	5.34	4.82	ATT= 0.52***	10.79
Non-innovators	7.54	4.98	ATU = 2.56***	51.41
Household income per AE (log)				
Innovators	5.86	5.37	ATT = 0.49***	9.12
Non-innovators	7.07	5.51	ATU = 1.56***	28.31
Consumption expenditure per AE (log)				
Innovators	6.54	6.24	ATT = 0.30***	4.81
Non-innovators	5.59	6.43	ATU = -0.84***	-13.06
Food gap/deficit (months)				
Innovators	2.59	3.71	ATT = -1.12***	0.30
Non-innovators	-0.83	3.00	ATU = -3.83***	-127.67
Household Hunger Scale (HHS) Score				
Innovators	1.03	1.53	ATT = -0.50***	-32.68
Non-innovators	1.25	1.21	ATU = 0.04	3.31
Food consumption expenditure per AE (log)				
Innovators	5.98	5.67	ATT = 0.31***	5.47
Non-innovators	5.16	5.90	ATU = -0.74***	-12.54
Household Dietary Diversity Score (HDDS)				
Innovators	7.30	8.02	ATT = -0.72***	-8.98
Non-innovators	6.07	7.03	ATU = -0.96***	-13.66

***, **, * represent 1%, 5%, and 10% significance level, respectively

7. Conclusion

We have analysed the effect of farmer innovation on household welfare, measured by farm and household income, consumption expenditure and food security. With this, we contribute to agricultural innovation literature since previous studies looking at the impact of agricultural innovations on household welfare have focused largely on externally promoted technologies. Using data from a recent field survey of rural farm households in northern Ghana and endogenous switching regression which controls for unobserved heterogeneity, we estimate the welfare benefits for both innovators from innovating (ATT), and non-innovators had they innovated (ATU).

The results show positive and significant welfare effects of farmer innovation, confirming the farmers' perceptions as well as the numerous anecdotal evidences on the significant role of farmer innovations in the livelihoods of rural farm households. First, we found that farmer innovation significantly improves both farm and household incomes per AE for innovators. Moreover, it positively increases household consumption expenditure per AE. Using both objective and subjective measures of food security, we also found that farmer innovation contributes significantly to the reduction of food insecurity among innovative households. Specifically, it significantly increases household food consumption expenditure per AE, and contributes substantially to the reduction of the length of food shortages as well as decreasing the severity of hunger among innovative households. However, we found that the positive productivity and income effects of farmer innovation do not significantly translate into nutritious diet, measured by household dietary diversity.

The ATU results show that farmer innovation would have heterogeneous effects on welfare of non-innovators, had they decided to innovate. Under current conditions, non-innovators will benefit from innovating in terms of farm and household incomes per AE and reduction in the length of food inadequacy in household, but would have been worse off with respect to food and consumption expenditure, and dietary diversity, had they innovated. This implies that in terms of meeting their consumption and food security needs, non-innovative households have better alternative sources.

Overall, the significance effect of innovation on both income and consumption and most of the food security indicators employed confirms the robustness of the positive effects of innovation on household well-being. The farmers' innovations reduce productions costs, increase revenue from crops and livestock production, minimise risks from climate and other external shocks and allow reallocation of labour to off-farm activities, resulting in the positive welfare outcomes observed. Our findings give credence to increasing assertions that farmer innovation has the potential of improving the livelihoods of rural households; hence, concerted policy efforts are needed to support and harness this potential. The significant contribution of farmer innovation to all the outcome indicators except dietary diversity suggests that more efforts are needed to ensure that the positive income effects translate into better nutrition for households in the study region. Thus, food security policies for the study region should go beyond food availability, and also focus on nutrition security.

It is important to emphasise that our findings do not imply the promotion of farmer innovation at the neglect of modern agricultural technologies. Farmer innovation cannot replace formal research. The findings on the heterogeneous welfare effects for non-innovators even suggest that farm households engage in other important activities which contribute to well-being; hence, the focus should not be solely on farmer innovation. Our results only strengthen arguments for better support for farmer innovation as a complement to externally promoted technologies in efforts to reduce poverty and attain food security.

We do not perform separate analyses for the different innovation domains or practices, as the samples are limited. However, it will be interesting to assess which specific types of farmer innovations contribute largely to household well-being. Future research comprising large sample size will permit such analysis. Also, innovation is generally a dynamic process so further research involving panel data would be needed to study the long-term effects of farmer innovation. This research uses data from only a small region of Ghana; hence, extrapolating the findings to other settings should be done cautiously. Nonetheless, our study have shown that rural poor farmers who are resource-constrained go beyond adoption of externally introduced technologies and implement their own cost-saving and environmentally sustainable farming system innovations which can contribute to household well-being.

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APPENDIX

Table A1: First stage results of the FIML ESR models

	(1)[a]	(2)	(3)	(4)	(5)	(6)	(7)
Information constraint	-0.323***	-0.399***	-0.260**	-0.272*	-0.390***	-0.268*	-0.434***
	(0.094)	(0.125)	(0.124)	(0.164)	(0.139)	(0.140)	(0.139)
Age	-0.006	-0.007	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Gender	-0.235	-0.291	-0.124	-0.249	-0.163	-0.170	-0.176
	(0.203)	(0.202)	(0.199)	(0.190)	(0.201)	(0.200)	(0.203)
Household size	-0.026	-0.024	-0.031	-0.027	-0.018	-0.032	-0.018
	(0.031)	(0.030)	(0.031)	(0.028)	(0.029)	(0.032)	(0.030)
Dependency ratio	-0.018	-0.008	0.036	0.035	-0.002	0.033	-0.001
	(0.092)	(0.091)	(0.091)	(0.089)	(0.092)	(0.094)	(0.091)
Education	0.018	0.034*	0.038**	0.039**	0.026	0.038**	0.030
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
FFF participation	0.069	0.220	0.352	0.400	0.213	0.337	0.154
	(0.304)	(0.304)	(0.305)	(0.321)	(0.300)	(0.313)	(0.309)
Land holding	0.037	0.052**	0.031	0.052**	0.042**	0.035*	0.045**
	(0.023)	(0.024)	(0.022)	(0.022)	(0.020)	(0.021)	(0.021)
Livestock holding	-0.030	-0.039*	-0.019	-0.018	-0.023	-0.023	-0.026
	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)
Assets value	0.015	0.006	0.003	0.003	0.006	0.004	0.004
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Off-farm activity	0.240	0.068	0.048	0.141	0.112	0.057	0.102
	(0.166)	(0.165)	(0.162)	(0.162)	(0.164)	(0.164)	(0.164)
Credit access	-0.071	-0.030	0.078	-0.050	0.043	0.055	0.014
	(0.154)	(0.156)	(0.156)	(0.161)	(0.157)	(0.157)	(0.159)
Road distance			0.026			0.056	0.062
			(0.083)			(0.081)	(0.082)
Group membership	0.421**	0.288*	0.304*	0.242	0.311*	0.294*	0.306*
	(0.179)	(0.175)	(0.170)	(0.168)	(0.173)	(0.171)	(0.174)
Climate shock	-0.252	-0.484**	-0.210	-0.263	-0.383*	-0.284	-0.397*
	(0.227)	(0.237)	(0.233)	(0.225)	(0.232)	(0.235)	(0.236)
Pest and disease shock	0.042	0.191	0.182	0.033	0.176	0.219	0.193
	(0.183)	(0.183)	(0.181)	(0.175)	(0.182)	(0.183)	(0.186)
Labour shock	-0.025	-0.150	-0.062	-0.103	-0.065	-0.096	-0.089
	(0.142)	(0.145)	(0.139)	(0.137)	(0.142)	(0.142)	(0.143)
Risk averse	-0.399***	-0.303**	-0.283**	-0.236*		-0.281**	-0.295**
	(0.138)	(0.138)	(0.135)	(0.136)		(0.136)	(0.138)
KNW District	0.076	-0.005	0.020	-0.012	0.053	0.039	0.075
	(0.214)	(0.210)	(0.205)	(0.210)	(0.205)	(0.210)	(0.207)
KNE District	-0.115	-0.216	-0.299	-0.115	-0.159	-0.224	-0.107
	(0.222)	(0.212)	(0.222)	(0.205)	(0.207)	(0.225)	(0.215)
Constant	0.349	0.734	0.235	0.341	0.244	0.265	0.386
	(0.521)	(0.522)	(0.523)	-0.507	-0.513	-0.535	-0.533

***, **, * represent 1%, 5%, and 10% significance level, respectively. Values in parentheses are standard errors.

[a] Models 1 to 7 refer to first-stage estimates for farm income, household income, consumption expenditure, food gap, HHS, food consumption expenditure and HDDS, respectively.