BUILDING FARMERS' CAPACITY FOR INNOVATION GENERATION: WHAT ARE THE DETERMINING FACTORS?

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Abstract

While farmers have been recognised as one of the key sources of innovation, many studies on agricultural innovations continue to consider farmers as adopters of externally-driven innovations only. Based on cross-sectional data from 409 farm households, this study, in contrast, analyses the innovation-generating behaviour among rural farmers in northern Ghana. Inspired by two innovation theories – induced innovation and innovation systems – we focus on the determinants of innovation behaviour. Employing recursive bivariate probit and endogenous treatment-regression models which control for selection bias, we find that participation in Farmer Field Fora, a participatory extension approach with elements of the innovation systems perspective, is a key determinant of innovation behaviour in farm households. Other important determinants are education, climate shocks and risk preferences. These results are robust to alternative specifications and estimation techniques.

Keywords: Determinants; Farmer Field Fora; farmer innovation; Ghana; innovation systems

1. Introduction

Innovation is essential for agricultural and economic development (Hayami and Ruttan 1985; World Bank 2011). The need to overcome challenges and harness opportunities has induced the development of several innovations in agriculture (Hayami and Ruttan 1985; Goldman 1993). However, the focus has mainly been on externally-driven technological innovations. Though there is a mounting body of evidences on the positive impacts of these technologies, the benefits are not realised by many smallholders whose adoption decisions are hampered by a number of constraints. These technologies are often unavailable, expensive for resource-poor farmers or require more complementary inputs (e.g. fertilizer) which may increase environmental problems (Chambers et al. 1989; Letty et al. 2011; Tambo and Abdoulaye 2012). Some authors have claimed that these technologies do not meet the needs of farmers or fit well into their farming systems but rather pose a threat to genetic diversity (Chambers et al. 1989; Reij and Waters-Bayer 2001). Moreover, the externally-driven technologies are often promoted using the transfer-of-technology (ToT) model. Some observers [e.g. Roling (2009a); Reij and Waters-Bayer (2001); Letty et al. (2011)] argue that the ToT model, which considers farmers as recipient of knowledge and fails to recognise their innovativeness, has led to the development of technologies that are inappropriate for farmers¡¦ conditions, hence, has not had the expected impacts. Unfortunately, there are still many evidences of the use of this model in Africa despite the increased recognition of the importance of strengthening the innovative capacity of farmers (Waters-Bayer et al. 2009; Brooks and Loevinsohn 2011; Letty et al. 2011).

Over the years, farmers have been recognised as innovators and experimenters and not just adopters of introduced technologies. In fact, farmers have been innovating long before the emergence of formal research and development (Biggs 1981), and there are even claims that some of the technologies developed by scientists were actually based on ideas and practices of local farmers (Chambers et al. 1989; Rhoades 1989; Roling 2009b). In the face of increasing challenges, rural farmers are increasingly becoming innovate (Sanginga et al., 2009; Wettasinha et al. 2008). They engage in informal experimentation, develop new

technologies and modify or adapt external innovations to suit their local environments (Rej and Waters-Bayer 2001). Farmer innovation processes are claimed to be relatively inexpensive, easily accessible, locally appropriate and highly disseminated (Rej et al. 2009; Waters-Bayer and Bayer 2009; Kummer 2010). Thus, farmer innovation could complement the highly promoted external innovations in addressing the increasing challenges confronting agriculture, and also contribute to sustainable intensification efforts.

In view of this, there has been some attention on promoting farmers innovations in recent years. For instance, the establishment of Prolinnova - a global learning network seeking to promote local innovation in ecologically-oriented agriculture and natural resource management- in 1999 has facilitated the identification and promotion of farmer innovations in several developing countries. While there is increased interest in promoting farmer innovations, little attention has been paid to what determines the innovation capacity of farmers. Despite the recognition of farmers as one of the sources of innovations, the plethora studies on innovative behaviour of farmers have focussed on adoption with little consideration for innovation generation. The few studies on the determinants of farmer innovativeness (e.g. Reij and Waters-Bayer, 2001; Nielsen, 2001; Kummer 2010; Mckenzie 2011), are qualitative if not anecdotal. In this paper, we attempt to address this gap in the innovation literature by assessing the determinants of innovation generation behaviour of farm households using econometric techniques. This is essential for policy efforts aiming at promoting farmer innovation, strengthening innovation capacity of farm households, and sustainable intensification.

In examining the determinants of innovation generation[1], we rely on elements of the induced innovation hypothesis and the innovation systems perspective. The induced innovation hypothesis considers challenges and opportunities as key drivers of innovation, whereas the innovation systems approach argues that innovations emerge through networks of actors and organizations. We particularly focussed on farm households' participation in farmer field fora (FFF), a participatory platform for enhancing innovation capacities, as a measure of the innovation system approach. To account for the possible selection bias from the non-random nature of the FFF participation, endogenous treatment-regression and recursive bivariate probit models are used in estimating the determinants of farmer innovative behaviour. The analyses are based on farm household data obtained from rural northern Ghana, which is an interesting case study. On the one hand, northern Ghana is characterised with resource-poor farmers who face challenges of climate change, soil infertility, land degradation, pest and diseases, population pressure and food insecurity, and thus serves as an appropriate example for analysing the induced innovation hypothesis. On the other hand, there are FFF programmes in the region which can be used in studying the effects of innovation systems in building farmers innovation capacity.

The remainder of this paper is structured as follows. We explain the methodology in the next section. Here, we describe in detail the estimation approaches, the data used for the analyses and also present some descriptive statistics. The results and discussion are presented in section 3. We first highlight the determinants of innovation generation and then present alternative estimation methods. Finally, section 4 concludes this paper.

[1] Innovation generation, innovation capacity and farmer innovation are used interchangeably in this paper. 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.

2. Methods

2.1 Empirical strategy

We are interested in estimating the determinants of innovation generation behaviour of farm households. This can be specified as:

$$FI_i = \beta_0 + \beta_1 X_i + \beta_2 \mathrm{II}_i + \beta_3 FFF_i + \beta_4 R_i + \beta_5 V_i + \varepsilon_i \qquad (1)$$

where the dependent variable *FI* (farmer innovation) indicates innovation generation behaviour of household *i*. We use four different measures of the dependent variable to check if the results are sensitive to the indicator employed. The first (*innovation_binary*) is a binary variable which is equal to one if the household has in the past 12 months, implemented any of the four categories of farmer innovation (i.e., invention of new practices or technologies, adaptation of exogenous ideas, modification common or traditional practices and experimentation of new ideas); and 0 otherwise. The second (*innovation_count*) is a count variable that indicates the number of different innovation generation activities implemented by a household in past 12 months. In the third and fourth measure of *FI*, we consider the varied importance of each of the four categories of farmer innovation and constructed innovation index using weights. In the third measure of *FI* (*innovation index 1*), we followed Filmer and Pritchett (2001) and used principal component analysis (PCA) to assign weights to each of the four innovation categories, and constructed a household innovation index. The final indicator (*innovation index 2*) also involves the construction of a household innovation index but using weights obtained through expert judgements. A stakeholder workshop was organised and 12 agricultural experts in the study region assigned weights to the four innovation categories based on agreed level of importance of each category. They assigned weights of 0.4, 0.2, 0.3 and 0.1 for invention, adaptation of exogenous ideas, modification of traditional practices and experimentation, respectively.

Variable *Xi* is a vector of household socio-demographic and economic variables that are commonly found in the agricultural innovation adoption literature (e.g. age, gender and education of the household head; household size and dependency ratio; access to services and the wealth position of the household). It also includes variables capturing land rights and soil fertility status of plots. The vector *II* contains variables motivated by the induced innovation hypothesis. It includes idiosyncratic shocks (such as climate, pest and diseases and labour shocks) experienced by the household during the past 5 years; household size change; and access to market opportunities. The variable FFF is equal to one if a household member participated in a FFF and zero otherwise, and we use it as a proxy for the innovation systems perspective.

Variable *R* represents household risk behaviour. Following the seminal study by Binswanger (1980), we conducted a simple experiment using the ordered lottery selection design with actual payment to elicit household risk preference. In the design, each respondent was presented with a choice of six lotteries, A-F and was asked to select one. Once chosen, a coin was tossed to decide the payoff. A higher payoff could only be obtained at the cost of a higher variance. For instance, option A is the safe option, offering an actual payment of 3 GH¢ while option F has the highest payoff of 8 GH¢ but with 50% probability of no payment. This design is most suitable and generates accurate result when the respondents are mostly illiterate or less skilled in mathematics as in our case (Harrison and

Rutström 2008). For the analyses, we use the six risk aversion classifications as shown in table AAA. Finally, we include village fixed effects (*V*) to control for unobserved heterogeneity in the sample villages. β and Ɛ are constant and random error term, respectively.

A usual problem of estimating equation 1 is the potential endogeneity of the FFF participation variable; hence, applying binary and count data regression models or ordinary least squares might yield biased estimates. There are two potential sources of endogeneity. First, there is placement endogeneity stemming from the non-random selection of FFF participating communities. Thus, if communities with more innovative farmers were selected to participate in the FFF, then the impact will be overestimated. Secondly, within the FFF participating communities, participation is voluntary; hence, farmers self-select to participate. Thus, participating farmers may differ systematically from nonparticipants in unobserved characteristics such as entrepreneurship, risk behaviour or motivation which might lead to biased estimates of the effect of FFF on innovation. Due to the endogeneity issues, participants and non-participants are not directly comparable. To deal with these problems, we use recursive bivariate probit (RBP) and endogenous treatment-regression (ETR) models and also exploited our sampling frame and data to control for relevant unobservables.

First, the non-participants sample was drawn from both FFF participating and non-participating villages, and this helps in reducing the problem of placement endogeneity. Though non-participants in FFF villages might potentially be affected by spillovers, we believe that participation enhances innovative generation capacity which is our outcome variable and exposure alone does not confer this skill. The non-participation villages were also drawn from the same agro-ecological zone and districts as the participation villages and are likely to be the next group of FFF villages in any future scaling up. Secondly, we use village fixed effects to account for unobservable heterogeneity between villages. Furthermore, through a simple experiment, we control for risk attitude of farmers which is one of the key unobservable characteristics of innovation studies but often not captured in many household surveys (Feder et al. 1985). Finally, we use initial regular sweet potato cultivation and initial membership of farmer group as instruments in RBP and ETR models to further remedy the endogeneity problems[2]. In the ETR models, we first estimate a selection model, expressed as:

$$FFF_i = \delta_0 + \delta_1 X_i + \delta_2 R_i + \delta_3 V_i + \delta_4 Z_i + \mu_i \qquad (2)$$

where *FFF, X, R* and *V* are defined as in equation 1. The vector *Z* consists of the two instruments: initial sweet potato cultivation and membership of farmer group. We argue that these two variables affect FFF participation but do not directly affect innovation generation behaviour. In the study region, sweet potato is a minor crop which is cultivated by almost every household, albeit irregularly and on a very small scale. Since participation in FFF is voluntary, every farmer could volunteer to join but we expect farmers who cultivate sweet potato at least two continuous cropping seasons prior to the FFF to show more interest in participating. Similarly, villages with regular sweet potato producers were more likely to be selected. Discussions with the FFF facilitators also indicated that, although not encouraged, extension officers responsible for registering interested participants appear to

[2] 'Initial' implies before the start of FFF in the participating villages and recent situation in non-participating villages. They are based on recall data.

have given preferences to farmer group members because they believed they were more likely to be committed to participate actively in the program.

One could argue that these instruments may be endogenous to the outcome variable. For instance, it is possible that unobserved factors such as motivation or ability that affect farmers decision to cultivate sweet potato regularly or join farmer groups prior to FFF also affect their innovation generation behaviour, leading to upward bias. Discussions with farmers (admittedly anecdotal) indicate that the motivation for cultivating sweet potato regularly and joining farmer group has nothing to do with innovation generation. Prior to FFF, the farmer groups were not active or engaging in any collective action that could induce innovation generation. Also, regular cultivation sweet potato seems unrelated to innovation as almost all the innovation generation activities observed are not connected to sweet potato production. Moreover, we use lagged variables of sweet potato cultivation and farmer group membership which are likely to be exogenous to recent innovation generation decision. Following Di Falco et al. (2011) and Fischer and Qaim (2012), we also estimated a placebo regression to test the exogeneity of our instruments. Using data from only non-participating villages, we examined the effect of the two instruments and other covariates on the innovation generation decision of households not exposed to FFF. We expect significant effects of the two instruments if they are endogenous to the innovation generation decision of households. We found that there is no direct effect of the two instruments on the outcome variable; hence, both variables are valid instruments. We will show in the results section that the two instruments also significantly affect FFF participation.

As already indicated, we use four different measures of the dependent variable to check if the results are robust to different specifications of innovation generation. We therefore require estimation techniques that account for the different measures of the dependent variable and the endogeneity of the FFF participation variable. Consequently, we use three different econometric techniques. In the first model, (*innovation binary)*, we estimate a maximum likelihood RBP with instruments because both the outcome and endogenous FFF participation variables are binary. In the second model (*innovation count)*, the outcome is a count variable so we employ a Poisson regression with endogenous treatment effects (PRETE). Finally, linear regression with endogenous treatment effects (LRETE) was used in estimating model 3 (*innovation index 1)* and model 4 (*innovation index 2)*[3]. For robustness checks, we also compute naïve models of equation 1 without accounting for the potential endogeneity of FFF participation. We also use a matching technique, PSM, as an alternative method to estimate the effect of FFF participation on innovation generation behaviour of farm households.

2.2 Data and descriptive statistics

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 between December 2012 and May 2013 in Bongo, Kassena Nankana East and Kassena Nankana West

[3] Models fit by PRETE and LRETE are referred to as ETR models (StataCorp 2013).

districts in Upper East Region, one of the poorest administrative regions of Ghana. The districts fall within the Sudan savanna agro-ecological zone which is characterised by systems of permanent cultivation on rain-fed land with high population density, small land holdings, soil degradation, low labour productivity, predominance of annual and biannual crops and increasing cash crop production (Ruthenberg 1971; Runge-Metzger and Diehl 1993). Agriculture is the main income source and cereal-legume cropping system is predominant in the study region. The major crops are millet, sorghum, maize, cowpea, rice and groundnut. Most households also rear livestock. The area is characterised by prolonged dry season and erratic rainfall; hence, many of the inhabitants migrate to southern Ghana to seek employment opportunities or engage in irrigated vegetable farming during the long dry season.

The sample included FFF participants, non-participants from FFF communities (hereafter, exposed farmers) and non-participants from control communities (hereafter, control farmers). We interviewed 409 households from 17 villages using a stratified random sampling. We first obtained from the district RTIMP project officers, a list of all the 24 villages in the three districts where FFF has been implemented between 2008 and 2011. Then we randomly selected 10 participating villages across the three districts. In each FFF, there were either 30 or 40 participants and we selected about 18 participants from each village, resulting in a total of 180 FFF participants. We also obtained a list of all households in each participating village and randomly selected 98 exposed farmers across the 10 villages. Since these exposed farmers are located in the same FFF villages, they may be potentially exposed to some of the effects of FFF. To obtain group of control farmers devoid of potential spillovers, we randomly selected seven villages from the three districts that have similar infrastructural services and socio-economic conditions with the FFF communities but far enough to be influenced by the FFF activities. Also, these control villages are possibly the next group of villages in any future scaling up the FFF programme. Out of these, we randomly selected 122 farm households from a household list obtained from the District Agricultural Offices. Thus, our final sample consists of 185 FFF participants and 224 non-participants (99 exposed and 125 control farmers), making a total of 409 sample farmers. The sampling of exposed and control farmers also allows us to estimate the spillover effects of FFF participation on farmer innovativeness.

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. The questionnaire captured data on household and plot characteristics, crop and livestock production, off-farm income earning activities, innovation-generation activities and access to infrastructural services, information and social interventions. The respondents were mainly FFF participants and household heads in the presence of other available household members.

Table 1 outlines the description of the variables used in the regression and their mean values. As explained earlier, four different specifications of the dependent variable are employed. The table shows that about 42 percent of the sample households conducted at least one innovation generation activity in the past 12 months. The explanatory variables consist of household and farm characteristics, participation in FFF, variables motivated by the induced innovation theory and risk preference. The explanatory variables also include village dummies to control for village fixed effects and the two instrumental variables, initial regular sweet potato cultivation and initial membership of farmer group.

Table 1: Description and descriptive statistics of variables

Variable	Description	Mean	SD
Dependent variable (farmer innovation)			
Innovation_binary	Household has conducted innovation generation activities (Binary)	0.42	0.41
Innovation _count	Number of innovation activities conducted by household (Count)	0.59	0.79
Innovation index 1	Household innovation index based on weights obtained through PCA	0.00	1.00
Innovation index 2	Household innovation index based on weights assigned by experts	0.13	0.21
Household and farm characteristics			
Age	Age of household head	49.42	14.88
Gender	Gender of household head (dummy, 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
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	Total value of non-land productive assets in 100 GH¢*	4.54	6.92
Off-farm activities	Household has access to off-farm income earning activities	0.76	0.43
Credit	Household has access to credit	0.26	0.43
Road distance	Distance to nearest all-weather road in km	0.54	0.84
Social group	Household member belongs to a non-farm group	0.40	0.49
Land right	Proportion of plots in which household has full user rights	0.86	0.25
Soil fertility	Proportion of plots with infertile soil	0.37	0.44
Innovation systems			
FFF participation	Household member participated in FFF	0.45	0.50
Induced innovation			
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
Household size change	Change in household size (between 2008 and 2012)	-0.35	2.13
Market opportunities	Household has improved access to markets in the past 5 years	0.50	0.50
Risk aversion category			
Extreme	Household is extreme risk averse	0.40	0.49
Severe	Household is severe risk averse	0.22	0.42
Intermediate	Household is intermediate risk averse	0.14	0.34
Moderate	Household is moderate risk averse	0.04	0.20
Slight to neutral	Household is slight to neutral risk neutral	0.11	0.32
Neutral to preferring	Household is risk neutral to preferring	0.09	0.30
Instruments			
Sweet potato	Household cultivates sweet potato regularly prior to FFF	0.69	0.38
Farmer group	Household member belongs to farmer group prior to FFF	0.33	0.43

* The exchange rate at the time of the survey was 1 euro = 2.5 GH¢

Figure 1 presents the share of households that implemented the four categories of innovation generation activities and compares the results between participants and non-participants. Informal experimentation, which was implemented by 25 percent of the sample households, constitutes the most practiced activity. Similar trend is observed when we compare the innovation activities of FFF participants and non-participants. This is

expected as experimentation is the first stage of most innovation processes. The figure also shows that relative to non-participants, FFF participants implemented more innovation generation activities in each of the the four categories which seems to suggest that FFF participation enhances innovation capacity. In the next section, we check if this relationship is causal using econometric techniques. Land preparation, method of planting, cropping pattern, soil fertility, new crops and varieties, soil and water conservartion and animal husbandry are the major areas of the farmers innovations, and most of them are yield-related. Examples of the farmer innovations include: informal trials or introduction of new crops or varieties (e.g. soy bean, plantain) in a community; testing and modification of planting distance and cropping pattern; using plant (e.g. Gloriosa) extracts as insecticide; new formulations of animal feed and new herbal remedies in the treatment of livestock diseases (ethnovertinary practices); developing and using new farming tools; storage of farm products using local grasses; and new methods of compost preparation.

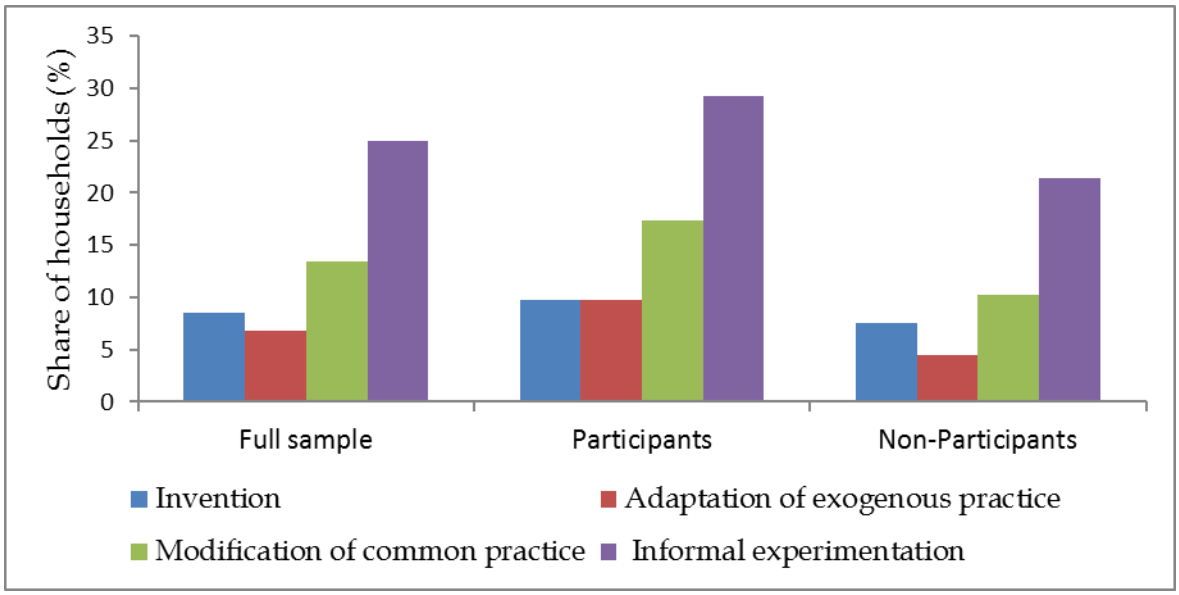

Figure 1: Share of households that implemented innovation generation activities

3. Results and Discussion

In this section, we look at the econometric results on the determinants of innovation generation. We check for robustness using alternative specifications.

3.1 Determinants of innovation generation

As already indicated, different econometric models (RBP and ETR) are used to deal with the endogeneity problems and also account for the distribution of the four dependent variables. We instrumented for the FFF participation in the first stage regression on the determinants of FFF participation. The two excluded instruments (initial farmer group membership and initial sweet potato cultivation) are highly significant in all models, which suggests the relevance of the instruments. The other variables that determine FFF participation are household size, social group membership and off-farm income[4]. The results of the estimated models on the determinants of innovation generation are presented in

[4] We do not show the first stage regression results for brevity.

Table 2. The Wald tests of independent equations indicate that there is a significant correlation between the error terms of the selection and the outcome equations in two of the models suggesting that there is a potential selectivity bias; hence, the use of treatment effect models is justified.

Table 2: Determinants of innovation generation behaviour

	Innovation (binary)	Innovation (count)	Innovation index 1	Innovation index 2
	RBP[b]	PRETE[c]	LRETE[d]	LRETE[d]
FFF Participation	0.223 (0.107)**	0.409 (0.168)**	0.655 (0.201)***	0.134 (0.039)***
Age	-0.003 (0.002)	-0.003 (0.003)	-0.004 (0.003)	0.000(0.001)
Gender	-0.084 (0.069	-0.143 (0.133)	-0.187 (0.140)	-0.013 (0.029)
Household size	-0.004 (0.011)	0.005 (0.020)	-0.000 (0.022)	-0.001 (0.005)
Dependency ratio	-0.010 (0.030)	-0.040 (0.058)	-0.055 (0.061)	-0.018 (0.013)
Education	0.013 (0.006)**	0.026 (0.011)**	0.035 (0.013)***	0.008 (0.003)***
Land holding	0.019 (0.007)***	0.017 (0.010)*	0.026 (0.013)**	0.005 (0.003)*
Livestock holding	-0.010 (0.008)	-0.016 (0.015)	-0.015 (0.017)	-0.006 (0.004)
Assets	0.002 (0.004)	0.006 (0.006)	0.000 (0.000)	0.000 (0.000)
Off-farm activities	0.041 (0.057)	0.140 (0.112)	0.160 (0.116)	0.041 (0.024)*
Credit access	0.057 (0.055)	0.087 (0.095)	0.149 (0.113)	0.016 (0.024)
Road distance	0.025 (0.030)	0.011 (0.056)	0.042 (0.062)	-0.001 (0.013)
Social group	0.004 (0.050)	-0.017 (0.091)	-0.083 (0.101)	-0.014 (0.021)
Land right	-0.054 (0.099)	0.057 (0.182)	0.081 (0.197)	0.038 (0.0415)
Soil fertility	-0.004 (0.059)	-0.009 (0.111)	-0.022 (0.118)	-0.022 (0.025)
Climate shock	-0.174 (0.085)**	-0.265 (0.144)*	-0.469 (0.173)***	-0.086 (0.037)**
Pest and disease shock	0.116 (0.065)*	0.165 (0.124)	0.192 (0.128)	0.020 (0.027)
Labour shock	-0.081 (0.050)	-0.085 (0.091)	-0.041 (0.099)	-0.011 (0.021)
Household size change	-0.019 (0.011)*	-0.037 (0.020)*	-0.061 (0.023)***	-0.008 (0.005)
Market opportunities	-0.012 (0.030)	-0.033 (0.054)	-0.030 (0.060)	-0.033 (0.013)
Severe risk averse (RA)	0.060 (0.062)	0.150 (0.118)	0.126 (0.122)	0.021 (0.026)
Intermediate RA	-0.008 (0.075)	-0.014 (0.149)	-0.008 (0.147)	-0.001 (0.031)
Moderate RA	0.217 (0.119)*	0.301 (0.193)	0.344 (0.244)	0.082 (0.051)
Slight to neutral RA	0.084 (0.077)	0.225 (0.139)	0.339 (0.159)**	0.088 (0.033)***
Neutral to risk preferring	0.190 (0.082)**	0.314 (0.136)**	0.463 (0.167)***	0.105 (0.035)***
Village fixed effects	Yes	Yes	Yes	Yes
Constant	0.309 (0.698)	-0.607 (0.735)	0.130 (0.457)	0.094 (0.096)
No. of observations	409	409	409	409
Wald (Chi^2)[a]	0.863	-	5.28**	6.22**

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

[a] We do not report the Wald (Chi^2) for the PRETE model because the first stage regression failed to completely converge

[b] We report the average marginal effects which were obtained using the stata command, margins with the option predict (pmarg1) force

[c] The PRETE model was estimated using *etpoisson* command in stata 13. Average treatment effects (ATE) are reported

[d] The LRETE model was estimated using *etpoisson* command in stata 13. The values are both ATE and average treatment on the treated (ATT) since we did not interact FFF participation variable with any of the outcome covariates (Statacorp 2013)

The results indicate that the determinants of innovation capacity are FFF participation, level of education of household head, size of land holding, household experience of climate

shock, change in household size and risk preference. This result appears to be consistent irrespective of the measure of innovation capacity employed. A key variable of interest, FFF participation, which is use to capture the innovation systems perspective is highly significant in all the four models. Participation in FFF is found to increase innovation generation by 22.3 percentage points, and FFF participants are also likely to implement 0.41 innovation generation activities relative to non-participants. There are three possible pathways through which FFF participation may influence innovation capacity. First, FFF provides opportunity for farmers to test their innovations in the presence of other stakeholders, and this builds their self-esteem and empowers them to innovate due to the recognition and appreciation of their ideas and practices by scientists. Secondly, FFF may enhance the analytical and problem-solving skills of participants which are essential for innovation and finally, the FFF graduates form vibrant farmer groups for continuous group discussion and learning which may facilitate further innovative activities. This result suggests that the concept of innovation systems which facilitates active interactions among key stakeholders has a potential for strengthening farmers' innovation capacity. The result also supports evidences of positive effects of FFS participation on adoption of agricultural innovations (e.g. Erbaugh et al. 2010; Friis-Hansen and Duveskog 2012; Lilleør and Larsen 2013). Education is another important determinant of innovation capacity as shown by its significant positive effect in all the four models. An additional year of education of household head increases household innovation practices by 2.6 percent. The significant and positive effects of both FFF participation and education confirm the important role of human capital formation in innovation.

Two of the variables motivated by the induced innovation theory, change in household size and climate shocks are statistically significant, albeit with a sign contrary to our expectations in the latter. While arguments of the induced innovation hypothesis suggest that households who are affected by climate-related shocks are likely to be innovative, the results suggest otherwise. This is, however, plausible as climate-resilient households may have better capabilities of implementing innovations. Among the four wealth-related factors included in the models, only size of land holding is a significant determinant of innovation generation. Most large land holders have several plots, hence, have the leverage to carry out experiments on some of them. There is no active land market in the study region so it is possible that the significance of land holding may rather be related to the opportunity it offers for experimentation. This result suggests that both resource-rich and resource-poor households generate innovations. This is an interesting finding because studies (e.g. Tambo and Abdoulaye 2012) have shown that resource-poor farm households are less likely to be adopt agricultural technologies because of the costs involved in accessing these technologies. Finally, the results show that compared to risk averse farmers, risk neutral and risk preferring farmers are more likely to be innovative. This is expected since innovations generally involve risk (Feder et al. 1985).

As a robustness check, we also estimate three naïve models of the determinants of innovation capacity[5] and compare the results with the RBP result in Table 2. First, we estimate a probit model (model 1) which ignores self-selection and placement bias. This is the preferred model assuming FFF participation is exogenous, hence, allows us to examine if the two-stage approach used above significantly changes the result of other exogenous variables of interest. The result shows that FFF participation increases innovation generation

[5] We do not show these results for brevity.

by 12.7 percentage points, thus indicating a downward bias if FFF participation is treated as exogenous. The direction and significance level of the other covariates, however, does not differ largely from those in Table 2. In model 2, we control for placement bias but assume no self-selection into FFF. Here again, we find that the innovation generation effect of FFF (13.2 percentage points) seems to be underestimated. Finally in model 3, we assume random village placement of FFF but account for potential self-selection into FFF. The result shows that FFF participants are 23 percentage points more likely to implement innovation generation activities relative to non-participants, which suggests a slight upward bias. The results from these three models suggest that the positive and significant effect of FFF on innovation generation behaviour is consistent and robust, but without controlling for self-selection and placement bias, the effect appears to be over-or underestimated.

4. Conclusion

There is no doubt that innovation is essential in this rapidly changing economic environment. While farmers have been recognised as one of the key sources of innovation and there are calls for strengthening their innovation capacities, many studies on agricultural innovations continue to focus only on externally-driven innovations and most of them consider farmers as adopters of introduced technologies. Based on cross-sectional household data from 409 farm households, this study analyses the innovation generation activities among rural farmers in northern Ghana. We specifically look at the determinants of innovation capacity in farm households using inspiration from two innovation generation theories: induced innovation and innovation systems.

This study has shown that resource-poor farmers are capable of implementing innovation generation activities. The innovations range from experimenting with new ideas, modifying or adding value to existing or external practices to complete discovery of better farming practices. Controlling for selection bias, we found that participation in FFF, a participatory extension approach with concepts of the innovation systems perspective, is a key determinant of innovation capacity in farm households. This is possible because participants are likely to be empowered and also gain problem-solving and analytical skills which are essential for innovation. This result is robust to alternative specifications and estimation techniques. The probability of implementing innovations also increases significantly with education, and together with FFF participation, they confirm the positive effect of human capital development on innovation.

In contrast to the innovation adoption literature where it is often argued that innovations are not pro-poor, our findings seem to suggest that wealth does not to play a key role in innovation generation decisions of farmers. We also found little evidence that shocks induce innovativeness. Climate shocks rather appear to reduce the probability of generating innovation. A possible explanation is that coping with such shocks may involve reallocating household resources (e.g. to non-farm employment) resulting in decreased agricultural production, hence, the less likelihood of generating innovations. Measuring risk is very difficult so it is often omitted in many innovation studies (Feder et al. 1985), but this study attempted controlling for farmers' risk attitudes and found that it is a very important determinant of innovation capacity in farm households.

This paper has shown that FFF is important for innovation; hence, policy efforts aiming at strengthening farmers' innovation capacity should provide platforms for active interaction among stakeholders as argued by the innovation systems theory. A good example will be the innovation platform by the Forum for Agricultural Research in Africa

(FARA) which facilitates interactions among actors who have a common interest in innovation generation (Nederlof et al. 2011). This does not imply that promoting FFF or its variants will definitely induce innovation generation behaviour in farmers. There are claims that some FFSs have rather been used as means to facilitate the transfer of technologies to farmers (Röling 2009a). The findings of this study only suggest that innovation generation policy towards farmers should focus on education, and institutional arrangements that permit interactions and learning among stakeholders with innovation capacity building as a key objective.

Farmer innovation is a continuous process, but this study is based on cross-sectional data which does not allow the analyses of these dynamics and is further challenged by endogeneity problems. While we have tried to address these issues by using robust estimation techniques, a more rigorous analysis will require the use of panel data; hence, future research in this direction will be useful in corroborating the findings of this study. Finally, there is increasing attempt to promote farmer innovations and this study has illustrated some necessary pathways. To further strengthen arguments in support of farmer innovations, studies on the impact of these innovations on the livelihood of farmers are needed. This is another gap in the literature for future research work.

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