Combining sustainable agricultural practices pays off: evidence on welfare effects from Northern Ghana

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Abstract

Sustainable agricultural practices are being promoted across Africa. While literature provides robust evidence on their welfare impacts in isolation, there is limited evidence on how combinations of sustainable agricultural practices contribute to households' welfare. Due to complementary and substitution effects and cost involved in adopting SAPs, combinations may have impacts that are higher or lower than individual effects. To shed light on this question we employ cross-sectional data from northern Ghana, which was collected from 421 households and 1229 plots. We investigate the adoption and impacts of sustainable agricultural practices (SAPs) on net crop income per acre and consumption expenditure per capita. We employed a maximum simulated likelihood estimation of a Multinomial Endogenous Treatment Effect Model (METEM) to account for observable and unobservable heterogeneity that influences SAP adoption decisions and the outcome variables. Our results reveal that adoption decisions are affected by household and plot level characteristics. We find that adoption of SAPs significantly increase net crop income and consumption expenditure except when soil & water conservation is adopted in isolation. Contrary to some previous studies elsewhere in Africa on this area, we find that SAPs have a stronger effect on income and expenditure when adopted as a package (all together) rather than in isolation or in sub groups.

Keywords: Net crop income; consumption expenditure; SAPs, multinomial endogenous treatment effect

1. Introduction

Feeding a surging population which is expected to double by 2050 (close to 2 billion) becomes a major agricultural research, development and policy challenge in Sub Saharan Africa (FAO, 2006). Improving agricultural production is widely regarded as a major objective through which the widespread lack of food security and poverty in Africa can be tackled and even eradicated (Future Agricultures, 2010). In effect, much emphasis has been given on how to transform the stagnant and low return of African agriculture into a more productive and dynamic sector. But emphasises should also be given to the protection of natural resources and ecosystems that could play a vital role in environmental regulation and mitigating the adverse effects of climate change. In fact, the literature points out that many ecosystem services like nitrogen fixation, nutrient cycling, soil regeneration, and biological control of pests and weeds, are under threat in key African food production systems (Jhamtani, 2011; Lee, 2005; Pretty, 1999; Woodfine, 2009).

Sustainable agricultural practices (SAPs) which include, improved crop varieties, complementary use of organic fertilisers, soil and water conservation structures, cereal-legumes rotation or intercropping, conservation tillage and residue retention, can address some of the environmental and ecosystem problems through sequestering soil carbon, improving soil fertility, and enhancing crop yields and incomes (Lee, 2005; Woodfine, 2009; Branca et al., 2011; Manda, et al., 2015; Teklewold, et al., 2013).

This study will focus on three SAPs: modern maize varieties, cereal-legumes rotation/intercropping and soil & water conservation structures. Having their roots in East Asia as a result of green revolution, improved varieties (e.g. maize varieties) have been one of the core development aspect of African agriculture. Teklewold et al., (2013) indicated that adoption of improved seeds is likely to be an important strategy in adaptation to future climate change, especially when it is combined with other SAPs like cereal- legumes rotation. Cereal-legumes rotation/intercropping have been proved to deliver many ecosystem services, including soil carbon sequestration, nitrogen fixation and breaking the life cycle of pests, improving weed suppression (Di Falco et al., 2010; Jhamtani, 2011; Tilman et al., 2002; Woodfine, 2009) while increasing crop yield. Teklewold et al., (2013) further reports that cereal-legumes rotation/intercropping can also reduce the use of chemical fertilizer and pesticides and hence contributes to mitigation of climate change. Adoption of soil & water conservation structures is another important aspect of SAP especially in areas where there is low distribution of rainfall as it can help increase soil moisture and reduces soil erosion. Review of empirical studies shows that farmers tend to take-up a single practice or combination of those agricultural practices.

There is a long established literature on the adoption of different single agricultural technologies and their impact on rural household's welfare. Previous empirical studies (e.g. Shiferaw et al., 2014; Abdulahi and Huffman, 2014; Kassie, et al., 2011; Olrinade, et al., 2011; Kassie, et al., 2014; Amare, et al., 2012; Asfaw, et al., 2012; Elias, et al., 2013; Becerril and Abdulai, 2010; Khonje, et al., 2015; Mendola, M, 2007; Minten and Barrett, 2008; Shiferaw, et al., 2008; Wu et al., 2010) have estimated the adoption and impact of single agricultural technologies on household welfare measured by outcomes like productivity, household income and food security. However, despite the potential complementarity or substitution among individual or combination of SAPs, very few studies have analysed the simultaneous adoption and impacts of SAPs on smallholder farmer's welfare. To our best knowledge, the only studies known to us to have analysed the adoption and impacts of individual and different combinations of SAPs on households' welfare are those by Teklewold, et al., (2013) in Ethiopia, Kassie, et al., (2014) and Mutenje, et al., (2016) in Malawi and Manda, et al (2015) in Zambia. However, Ghana might have different ecological set up and agricultural policies compared to Ethiopia, Malawi or Zambia, hence the adoption and impacts of SAPs could be different in the Ghanaian context. We also included soil & water conservation structure as one part of the SAPs considered as very little empirical evidence exists on the effects of soil & water conservation structure (especially in combination with other SAPs like improved maize seed varieties and cereal-legumes rotation/intercropping) on households' welfare.

The objective of this paper is therefore to identify the determinants and impacts of SAPs on rural households' welfare measured in net crop income and consumption expenditure. To address this objective we have specifically answered two questions: What are the effects of the determinants of adoption of single and combination[1] of SAPs and their impact on crop net income per acre and consumption expenditure per capita? What are the SAPs packages that yield the highest welfare effects? We have applied a maximum simulated likelihood estimation of a multinomial endogenous treatment effect model (METEM) to account for observable and unobservable heterogeneity to address our objective. We find that generally, SAPs increase rural households welfare and payoffs are higher when combinations of SAPs are adopted both at household and plot levels.

This paper contributes to the limited but emerging literature on the adoption and impacts of different packages of SAPs in Sub-Sharan Africa. We have also contributed to the literature by including a measure for the risk preference of sampled households. We accounted households' subjective risk preferences[2] using the Ordered Lottery Selection Design with real payoffs (Harrison and Rutström 2008). Previous studies (Binswanger 1980 and 1981, Wik and Holden, 1998, and Yesuf and Bluffstone, 2009) suggest that rural households in developing countries are generally risk averse. Despite this fact, however, very few studies have attempted to address the effect of risk aversion behaviour on adoption of agricultural innovations.

The rest of the paper is organized as follows: The next section outlines the data used and its source. The conceptual framework, model specification and estimation strategy applied in the study are presented in section three. Section four presents the descriptive statistics of the study. Result of the study and discussions are presented in section five. The last section concludes.

[1] We use the terms 'combination' and 'packages' interchangeably in this paper
[2] We identify the risk preference of households by playing a lottery game with real payoffs where a farmer could get from 0 up to maximum 8 Ghana Cedis (equal to 2 dollars).

2. Study Area, Data and Sampling Procedure

Our data comes from a survey of 421 farm households and 1229 plots conducted between April and July of 2015 in the Upper East Region of Ghana. Our study is part of the project West African Science Service Center for Climate Change and Adapted Land Use (WASCAL) currently running since 2010 in collaboration with the Center for Development Research (ZEF), University of Bonn and partners at ten West African countries.

The survey was conducted in four districts (Bongo, Bawku West , Kassena Nankana East and Bluilsa South) of the Upper East Region of Ghana. The region is characterized by its low income and most vulnerable region of Ghana to adverse effects of climate change. An extensive household survey with personal interviews and observations was prepared and administered by trained enumerators who had an earlier experience in data collection and who speak the local languages through personal interviews and observations. Community level data was also collected.

Stratified random sampling was used to select our sampled households. At first stage seven of the thirteen districts of the Upper East Region were identified based on their intensities of SAP use (specifically improved maize). From the seven identified districts, four districts were randomly selected. In the second stage seven[3] communities were randomly selected from each district. Finally, farm households were randomly selected from each selected community, with the number of households selected from each community being proportional to the size of the community.

In addition to the socio economic household characteristics (e.g highest education attained, age, gender, family size) we have also collected plot level data which includes land tenure of each plot, the distance of plot from homestead, fertility level of plot, size of plot and slope of plot. This allows us to estimate the Mundlak fixed effects using the mean value of plot-varying explanatory variables to in part control unobserved heterogeneity that may be correlated with observed explanatory variables. Data on expenditure, forest based income, crop yields and the use of SAP's such as improved maize verities, cereal-legume intercropping and or diversification and soil and water conservation structure were collected.

We have considered improved maize varieties (V), cereal-legume diversification (D) and soil & water conservation (C) as components of SAPs in this study. This results in eight possible combinations of SAPs which are, improved maize seed varieties only ($V_1C_0D_0$) , soil & water conservation only ($V_0C_1D_0$), cereal-legumes diversification only ($V_0C_0D_1$), improved maize varieties and soil & water conservation only ($V_1C_1D_0$), soil & water conservation and cereal-legume diversification only ($V_0C_1D_1$), improved maize varieties and cereal-legume diversification only ($V_1C_0D_1$), improved maize varieties, soil & water conservation and cereal-legume diversification ($V_1C_1D_1$) and finally the base category which constitutes none of the three SAPs ($V_0C_0D_0$). But we find that the improved maize varieties and soil & water

[3] Six communities were selected from the Bongo districts because the districts has bigger population than the others.

conservation only ($V_1C_1D_0$) SAP have been adopted by only nine plots and eight households. This shows we have got too few observations in this category such that treating it separately would make the model not to converge due to the negative degrees of freedom. Hence we have combined[4] this category with the soil & water conservation and cereal-legume diversification only ($V_1C_1D_0$) category, which leads us to have seven SAPs categories. The distribution of SAPs over plots and households[5] are presented in Table 1 below.

Table1: Distribution of SAPs packages on plot and household level

SAP Categories	HH freq	Per(%)	Cum.	Plot freq	Per(%)	Cum.
$V_0C_0D_0$	96	22.8	22.8	474	38.57	38.57
$V_1C_0D_0$	42	9.98	32.78	73	5.94	44.51
$V_0C_1D_0$	31	7.36	40.14	68	5.53	50.04
$V_0C_0D_1$	102	24.23	64.37	416	33.85	83.89
$V_1C_1D_0$ & $V_0C_1D_1$	40	9.5	73.87	86	7	90.89
$V_1C_0D_1$	51	12.11	85.99	72	5.86	96.75
$V_1C_1D_1$	59	14.01	100	40	3.25	100
Total	**421**	**100**		**1229**	**100**	

Source: authors estimation based on survey result

Table 1 above shows that 22.8 % of households and 38.57% of plots did not adopt any of the three SAPs. Cereal-legume diversification is the most common SAP practiced by households in the Upper East Region of Ghana, being practiced by 24.23% households and in 33.85% plots. The most comprehensive package ($V_1C_1D_1$) is adopted by 14.01% of households but this package is employed in only 3.23% of the 1229 plots.

3. Conceptual and Econometric Framework

Smallholder farm households produce and consume a number of crop varieties. Their decisions which crops to grow, which methods of production to follow and which combinations of SAP's to adopt can be explained by household economic theory (Becker, 1965). Several components of agricultural innovations are usually introduced in packages (Manda et al., 2015). The technologies could be substitutes or complements and their use and adoption depends on household specific observed and unobserved characteristics. Farmers normally adopt combinations of technologies in response to agricultural constraints such as drought, weeds, pest and diseases.

We assume that farmers' decision to adopt one of the above mentioned SAPs is affected by observable and unobservable characteristics. If our approach was a controlled experiment, the impacts of these SAPs would have be determined by simply comparing observable outcome variables across plots or households those adopting and non-adopting. But our study relies on observational data. Hence, farmers self-select to the adoption decision of SAPs and their decision is likely to be influenced by variables which are unobservable or impossible to quantify using standard household surveys (such as managerial skills and

[4] This method of combining different packages in the case of few observation in a certain packages have been used in the literature. For example, see Mutenje, et al., 2016 and Di Falco and Verona, 2013
[5] We consider household as an adopter if the household adopts at least in one of his plots

motivation). But these unobservable that may be correlated with the outcome variable of interest (net crop income and consumption expenditure). This necessitates a selection correction estimation method. We apply maximum simulated likelihood estimation of a multinomial endogenous treatment effect model to account for observed and unobserved heterogeneity.

In the first stage, the adoption decision to the SAPs packages is modelled in a mixed multinomial logit selection model. In the second stage, the impact of each SAPs on the outcome variables is estimated using ordinary least square (OLS) with selectivity correction terms.

3.1 Multinomial Endogenous Treatment Effect Model

The multinomial endogenous treatment effect model consists of two steps. In the first stage, a farmer choses one of the eight possible combinations of SAPs in a given plot or at the household level. Following Deb and Trivedi (2006), let V_{ij}^{*} be the latent variable that captures the expected net crop income revenue or expenditure per capita from adopting SAPs packages j (j=1….M) instead of implementing any other strategy k. We specify the latent variable as

$$V_{ij}^{*} = z_i^{'}\alpha_j + \sum_{k=1}^{J}\delta_{jk}l_{ik} + \eta_{ij} \qquad (1)$$

Where z_i is a vector exogenous socio economic, social capital, risk aversion and plot-level covariates that affect the decision to adopt a specific SAP's package and the outcome of interest, α_j is the vector of corresponding parameters to be estimated; η_{ij} are the independently and identically distributed error terms; l_{ik} is the latent factor that incorporates the unobserved characteristics common to the households implementation of SAPs and the outcome variables (Net crop income per plot and annual expenditure per capita), such as the technical abilities of the farmer in examining new technologies, imperfect rural labor market structure, information asymmetry and/or high transaction cost incurred (Mutenje et al., 2016; Manda et al, 2015; Abdulai and Huffman, 2014; Pender and Kerr, 1998). Following Deb and Trivedi (2006b), let j=0 represents non adopters of any of the SAPs and $V_{i0}^{*} = 0$. While V_{ij}^{*} is not observed, one can observe the choices of SAPs packages in the form of a set of binary variables and these are collected by a vector, $d_i = d_{i1}, d_{i2}, d_{i3}............d_{iJ.}$ Similarly, let $l_i = l_{i1}, l_{i2}, l_{i3}...., l_{iJ.}$ Then the probability of treatment can be written as:

$$\Pr(d_i | z_i, l_i) = g\left(z_i^{'}\alpha_1 + \sum_{k=1}^{J}\delta_{1k}l_{ik} + z_i^{'}\alpha_2 + \sum_{k=1}^{J}\delta_{2k}l_{ik} + ... + z_i^{'}\alpha_J + \sum_{k=1}^{J}\delta_{Jk}l_{ik} \right) \qquad (2)$$

Where g is an appropriate multinomial probability distribution. Following Deb and Trivedi (2006b), we posit that g has a mixed multinomial logit (MMNL) structure defined as:

$$\Pr(d_i | z_i, l_i) = \frac{\exp(z_i^{'}\alpha_j + \delta_j l_{ij})}{1 + \sum_{k=1}^{J} \exp(z_i^{'}\alpha_k + \delta_k l_{ik})} \quad (3)$$

In the second stage, we investigate the impact of adopting the SAPs packages on two outcome variables: the natural logarithm of net crop income and total household consumption expenditure per capita. The expected outcome equation is formulated as follows:

$$E(y_i | d_i, x_i, l_i) = x_i^{'}\beta + \sum_{j=1}^{J} \gamma_j d_{ij} + \sum_{j=1}^{J} \lambda_j l_{ij} \quad (4)$$

In the above equation y_i is the welfare outcome measures, net crop income per acre and consumption expenditure per capita, for a household i; x_i represents exogenous covariates with parameter vectors β. Parameters γ_j represents the treatment effects relative to the non-adopters. Specifically, coefficients γ_j indicates the impacts of SAPs on the welfare of farm households. Since $E(y_i | d_i, x_i, l_i)$ is a function of the latent factors l_i, the outcome variables are affected by unobserved characteristics that potentials also affect the selection in to treatments. It is also important to note that when the factor-loading parameters (λ_j), is positive (negative), treatment and outcome are positively (negatively) correlated through unobservable characteristic, i.e there is positive (negative) selection, with γ and λ the associated parameter vectors, respectively (Manda, et al., 2015). Because our outcome variable are continuous, we follow a normal (Gaussian) distribution function. The model was estimated with Maximum Simulated Likelihood (MSL) method.

Parameters of the fitted model can be identified even an excursion restriction variable is not included in the treatment equation. But Deb and Trivedi (2006) recommend the use of at least one exclusion restriction or treatment variable for a more robust identification. As previous studies indicated (Manda, et al., 2015; Teklewold et al., 2013; Di Falco, et al., 2011) getting a valid instrument is theoretically and empirically challenging. We used previous information or training about SAPs as an instrumental variable. Our instrumental variable is a binary variable which takes one if a sampled household had information or prior training about SAPs in a demonstrations plots, and zero if no information or training on SAPs was obtained. Though in most cases the primary sources of information is usually through government extension agents, demonstration plots are also important sources of information on improved agricultural technologies' (Manda, et al., 2015). In addition, in our study area, there have been a demonstration training programs in the past, for example through Root and Tuber Improvement and Marketing Programme (RTIMP) in the Farmers Field Fora (FFF) framework, where farmers are grouped and demonstrate about agricultural activities were given. Information or previous training about SAPs is likely to enhance SAPs adoption but is unlikely to have any direct effects on net crop income or household consumption per capita unless through adoption of SAPs for the adopter sub-sample households. Previous studies in Africa have proven information or training about SAPs can be used as a valid instrumental variable (Di Falco et al, 2011; Di Falco and Veronesi, 2012; Manda, et al, 2015). Following

(Di Falco, et al, 2011) we conducted the admissibility test of the instrument by performing a simple falsification test. According to this test, a variable is a valid instrumental variable if it affects the decision of adopting SAPs equations, but will not affect the outcome variables among only the non-adopting sub-samples (Di Falco et al, 2011; Di Falco and Veronesi, 2013). Results show that (Table 6 in the appendix) information or previous training on SAPs is statistically significant among most of the adoption equations and is not statistically significant in the outcome variables for the non-adopting sub-sample households suggesting that our instrument is valid.

Most importantly, we exploit plot-level characteristics to deal with farmers' unabsorbed effects such as their innate abilities. Plot specific information can be used to construct a panel data and can be helped to control for farm specific unobservable (Udry, 1996). Including standard fixed effects, where farm specific variables are created in deviations from their averages, is, however, complex in a multinomial treatment effect approach. We therefore, follow Mundlak (1978) approach to control for unobservable characteristics. We exploit the plot level information and insert the mean values of the plot specific characteristics in our multinomial equation.

4. Variables and Descriptive Statistics

The outcome variables used in this studies are net crop revenue per acre and total consumption expenditure per capita in the 2014/15 agricultural season. Unlike previous studies (Mutenje, et al., 2016 and Manda, et al., 2015) who used maize yield per hectare or Teklewold et al., 2013, who used only maize income per hectare, we have used total net crop income per acre as an outcome variable because our study subjects happen to cultivate multiple crops together. The net crop revenue was chosen, as the use of SAPs may also affect the household resource allocation among crop production ventures. All crops produced by the household in a certain plot was valued at market price and all variable inputs such as cost of fertilizer, seed, hired labour, ploughing and manure used were deducted. Finally, the net revenue of crops were divided by the total plot size to get the net crop revenue per acre. We have also used per capita consumption expenditure in favour of per capita income, because it is more reliable (Deaton 1997). A 7-day recall period was used to capture food expenditure by the household, 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 converted in to their respective total annual consumption levels. The total annual household consumption expenditure were standardized in to per adult equivalent terms.

Our empirical model relies on a review of similar adoption and impact empirical studies (Di Falco and Verona, 2013; Di Falco et al, 2011; Kassie et al., 2010, 2011; Manda, et al., 2015; Mutenje, et al., 2016; Neill and Lee, 2001; Teklewold et al., 2013; Wollni et al., 2010). Previous studies suggest that many factors affect the adoption decision and intern affect the outcome variables. Those factors include household characteristics (such as age of the head, education level of the head of the household, family size and gender); resources ownership and market access (such as total livestock holdings, total asset, total cultivable land, distance to input market, credit constraint); social capital and information (membership in farmers association, number of relatives and friends that the household relies on times of difficulties or events within and outside the community, extension contacts, climate change awareness), plot specific characteristics (distance of plots from homestead, land tenure security of plots, self-reported slop, as well as fertility of plots); household risk preferences (which we have captured using an experiment with actual payments) and geographic locations (which we have captured using district dummies). Results of the descriptive statistics are presented in Table 2 below.

Table 2: Descriptive Statistics of the Variables included in the model

Variable	Variable description	Mean values for SAP package						mean of all SAPs	SD of all SAPs
		$V_1C_0D_0$	$V_0C_1D_0$	$V_0C_0D_1$	$V_1C_1D_0$ / $V_0C_1D_1$	$V_1C_0D_1$	$V_1C_1D_1$		
Household Characteristics									
AGE	Age of the Head	50.94**	51.98*	52.48**	55.11	50.2**	56.35	53.52	0.4
MHEAD	1=if head of the hh is male	0.92**	0.76	0.84	0.8	0.8	0.97***	0.83	0.01
FSIZE	Family size of the hh	7.1	7.74	6.62**	7.77*	6.43*	6.17**	6.95	0.08
EDUHEAD	Years of education of head	2.97***	1.62*	2.24***	2.18***	2.31***	1.75	1.78	0.09
Resources Constraints and market access									
DISINPUT	Walking distance to input market	99.08	97	113.16	93.58**	104.25	93.775	108.17	2.08
CREDIT	1=Credit constrained (credit is needed but unable to get it	0.19	0.34*	0.13***	0.07***	0.24	0.125	0.189	0.01
Ln_ASSET	ln value of total Asset	7.63	7.84**	7.74***	7.88***	8.05***	7.98***	7.69	0.02
TLU	Total livestock holdings in TLU	5.62	4.97	5.36	5.99*	6.8***	6.6**	5.3	0.18
LTCL	ln value of total cultivated land holding	1.83	1.82	1.87	1.79	1.78	1.91	1.84	0.015
DSHOCK	1= if household has lost hh member or relative in the past 5 years	0.55	0.71	0.55**	0.67	0.6	0.65	0.6	0.013
Social Capital and Information									
GROUPM	1=if hh belongs to any group	0.53***	0.47**	0.4**	0.49***	0.65***	0.65***	0.41	0.014
V_KINSHIP	number of relatives in the same community	4.34	4.26	4.18	4.1	5.61**	5.625**	4.16	0.16
NV_KINSHIP	number of relatives in outside the village	2.11	3.37**	4.55***	3.08**	4.36***	1.45	3.1	0.18
EXT	1= if hh had any contact with extension worker	0.73***	0.71***	0.46	0.64***	0.64**	0.7***	0.527	0.014
CCHANGE	1= if hh is aware about climate change	0.91	0.97**	0.95***	0.98***	0.94	0.975*	0.92	0.007
Mundlack fixed effects									
LP_DIS	ln mean distance of plot from home	6.41	6.44	6.05*	6.03	6.15	5.96	6.19	0.05
AP_TENURE	mean of plot land tenure security	0.92	0.91	0.92	0.94*	0.88	0.93	0.91	0.005
ALOWFER	mean value of low fertile plots[a]	0.29	0.17***	0.26***	0.17***	0.24**	0.202**	0.29	0.01
AMODFER	mean value of moderate fertile plots	0.58	0.68***	0.6***	0.66***	0.59	0.59	0.57	0.01
AHIGFER	mean value of high fertile plots	0.12	0.14	0.13	0.16	0.18	0.21**	0.13	0.007
ASTESLO	mean value of step slop plots[b]	0.03	0.18***	0.06**	0.07*	0.08**	0.05	0.06	0.004
AMODSLO	mean value of moderate slop plots	0.23**	0.34	0.35	0.25**	0.35	0.25	0.33	0.01
AFLASLO	mean value of flat slop plots	0.74***	0.48***	0.59	0.68	0.57	0.7	0.61	0.01
Risk preference									
EXT_RP	1=Extreme risk preference	0.12**	0.26	0.18*	0.19	0.11**	0.05***	0.19	0.011
SEV_RP	1=Sever risk preference	0.16	0.07**	0.16	0.09*	0.18	0.1	0.15	0.01
MOD_RP	1= Moderate risk preference	0.18	0.04**	0.13	0.104	0.15	0.15	0.14	0.009

INT_RP	1=Intermediate risk preference	0.2	0.2	0.1***	0.13**	0.1**	0.075**	0.16	0.01
SLI_RP	1=Slight risk preference	0.14	0.09	0.2***	0.16*	0.17*	0.1	0.14	0.009
NEU_RP	1=Neutral risk preference	0.19	0.32***	0.22***	0.32***	0.29***	0.52***	0.22	0.01
SAP_Inf	1= if hh had information about or training on SAPs	0.73***	0.63***	0.49***	0.73***	0.71***	0.75***	0.51	0.01
N	Number of Observations	73	68	416	86	72	40	1229	

Note: each SAPs packages are compared with the base category (non-adopters) ($V_0C_0D_0$) which has 474 observations at plot level.*, **, *** denotes significance level at 10%, 5% and 1% respectively. [a] farmer ranked each plot as "low fertile" medium fertile" and "high fertile". [b] farmer ranked each plot as 'step' , 'moderate step' and 'flat' slope

5. Results and Discussion

In this section, we first investigate the factors affecting the adoption of single and combinations of SAPs and then the implication of adopting a particular SAP package on plot and household level using net crop income per acre and per capita consumption expenditure. The mixed multinomial logit model was used to investigate the determinants of single and combination of SAPs.

5.1 Determinants of Adoption of SAPs

Parameter estimates of the mixed multinomial logit model of the plot and household level[6] determinants of SAPs adoption are presented in Table 3 and Table 5. The base category is non-adoption of the SAPs indicated in a given plot and in any plots owned at household level. The model fits the data very well with the Wald test, $\chi^2 = 1217.37$; $P > \chi^2 = 0.000$ and $\chi^2 = 1278.20$; $P > \chi^2 = 0.000$ for the plot and household level, respectively, indicating that the null hypothesis that all the regression coefficients are jointly equal to zero should be rejected.

Our results show that age has a significant negative effect in adopting only improved maize varieties package both at plot and household level adoption decision. Our results are consistent with previous studies who find age to have a negative effect on technology adoptions (Di Falco and Verona, 2013; Teklewold, et al., 2013) but contrary to the findings of Kassie et al., (2014) who find age to have a positive effect on SAPs adoption. Our results also suggest that gender of headed of the household is negatively related with adoption of SAPs.

We find a positive effect of family size on the soil & water conservation with cereal-legume diversification or improved seed package (V1C1D0 / V0C1D1). This could be due to the fact that soil & water conservation structure is labour demanding and hence positively associated with family size. We also find family size to have a negative effect on the cereal-legume, improved seed and cereal-legume as well as the combination of all three SAPs. This is consistent with the findings of Kassie et al., (2014), who reports family size to be negatively and significantly correlated with maize- legume diversification.

[6] The results for the household level determinants are presented in table 5 in the appendix

As expected, we find a positive and significant effects of education in most of the SAPs both at the household and plot level adoptions. Education plays a vital role in understanding agricultural innovations and in processing available information about new innovation. This is consistent with previous studies (Kassie et al., 2014; Manda, et al., 2015; Mutenje, et al; 2016).

Table 3 results show that distance to input market is negatively associated with the adoption of SAPs and is significantly related with the soil and water conservation with improved maize varieties or cereal-legume diversification package at the plot level adoption. As expected credit constraint is negatively and significantly associated with the adoption of most of the SAPs packages. Specifically, credit constraint is negatively related with improved maize varieties only, cereal-legume diversification only, soil & water conservation with improved maize varieties or cereal-legume diversification as well as with all the comprehensive three packages. This is consistent with the fact that credit constraint is one of the bottle necks of technology adoption in Sub-Sharan Africa. Our results are consistent with to those findings by Teklewold, et al., (2013). We find that total asset holdings to have a positive effect on SAPs adoption. We find that total cultivated land holdings to be associated negatively with the adoption of improved maize varieties only ($V_1C_0D_0$) and the soil & water conservation with cereal-legume diversification or improved seed packages ($V_1C_1D_0/V_0C_1D_1$). Teklewold, et al, (2013) finds similar results and argues that it could be because smaller holder farmers tend to achieve food security by sustainably intensifying production in their small lands.

Membership in farmers association or group increased the adoption of improved maize varieties and cereal-legume diversification ($V_1C_0D_1$). Membership in farmers group is an important source of information, input and innovation (Mutenje, et al., 2016). We find a mixed effect of village and non-village kinships on the adoption of technologies. Village kinship is strongly associated with the adoption of all SAPs at a time but negatively related with the package cereal-legumes diversification only ($V_0C_0D_1$) non-village kinship is positively associated with the adoption of soil & water conservation technologies ($V_0C_1D_0$), cereal-legume diversification only ($V_0C_0D_1$), soil & water conservation with cereal-legume diversification or improved maize varieties ($V_1C_1D_0/V_0C_1D_1$) and the improved maize varieties and cereal-legume diversification($V_1C_0D_1$), but negatively related to with the adoption of all SAPs ($V_1C_1D_1$). Our results of the mixed effects of social capital are in line with those findings by Di Falco and Bulte, (2013) which finds that kinships in the form of relatives are negatively related with soil & water conservation but positively related with tree planting. The negative effect of social networks could be due to the fact that compulsory sharing with in networks could lead to free riding and could limit incentives to adoption SAPs.

Climate change awareness is strongly and significantly associated with the packages cereal-legume diversification ($V_0C_0D_1$) and improved seed and cereal-legume diversification ($V_1C_0D_1$). This highlights the importance of upgrading the climate change awareness to adoption of SAPs

Furthermore, we exploit plot level characteristics to control in part the issue of unobservable heterogeneity such as hidden abilities of households. As expected, distance of plot from homestead has a negative and significant effect on the comprehensive ($V_1C_1D_1$) package. Tenure security improves the adoption cereal-legume diversification ($V_0C_0D_1$) and soil & water conservation with improved maize varieties or cereal-legume diversification ($V_0C_0D_1$/ $V_0C_0D_1$). This supports the hypothesis that land investment such as on soil & water conservation increases with secure land tenure than otherwise. Having moderate or fertile plot is associated with almost all SAPs packages. Flat slope and moderate slope are likely to reduce the adoption of SAPs that involve soil & water conservation (both in isolation and jointly with other SAPs) than those with steep slope plots.

Interestingly, our results show that risk neutral households are more likely to adopt comprehensive SAPs as compared to risk averse households. Specifically, risk neural households are more likely to adopt SAP like packages cereal-legume diversification ($V_0C_0D_1$), soil &water conservation with cereal-legume diversification or with improved maize varieties ($V_1C_1D_0$ / $V_0C_1D_1$), improved maize varieties with cereal0legume diversification ($V_1C_0D_1$) and all the three SAPs together ($V_1C_1D_1$)than risk averse households. This suggests the importance of reducing risks exposure through, for example, farm insurances to enhance SAPs adoption rates.

Table 3: Mixed Multinomial Logit model estimates of adoption of SAPs in Upper east Region of Ghana (baseline category is non-adoption of SAPs)

VARIABLES	(1) $V_1C_0D_0$	(2) $V_0C_1D_0$	(3) $V_0C_0D_1$	(4) $V_1C_1D_0$ /$V_0C_1D_1$	(5) $V_1C_0D_1$	(6) $V_1C_1D_1$
Household Characteristics						
AGE	-0.0198*	0.000232	-0.00923	-0.00120	-0.00766	0.00878
	(0.0109)	(0.0132)	(0.00687)	(0.0128)	(0.0131)	(0.0163)
MHEAD	0.830	-0.815*	-0.430*	-1.478***	0.00733	1.469
	(0.541)	(0.452)	(0.244)	(0.437)	(0.513)	(1.079)
FSIZE	0.0162	0.0304	-0.0967***	0.128**	-0.161***	-0.188**
	(0.0645)	(0.0590)	(0.0346)	(0.0600)	(0.0584)	(0.0909)
EDUHEAD	0.103**	0.0244	0.118***	0.187***	0.0299	0.0947
	(0.0412)	(0.0679)	(0.0324)	(0.0552)	(0.0580)	(0.0863)
Resource Constraints and market access						
DISINPUT	-0.00161	-0.00196	0.00129	-0.00354*	-0.000124	-0.00368
	(0.00187)	(0.00284)	(0.00124)	(0.00212)	(0.00231)	(0.00254)
CREDIT	-0.707*	0.315	-1.171***	-2.185***	-0.534	-1.051*
	(0.423)	(0.358)	(0.247)	(0.479)	(0.466)	(0.598)
Ln_ASSET	0.130	0.308	0.296**	0.663**	0.540**	0.396
	(0.207)	(0.236)	(0.123)	(0.258)	(0.218)	(0.347)
TLU	0.0189	-0.0184	0.00443	0.0237	0.0367	0.0188
	(0.0260)	(0.0281)	(0.0167)	(0.0273)	(0.0232)	(0.0259)
LTCL	-0.559*	-0.350	0.158	-0.664**	-0.193	0.0107
	(0.300)	(0.373)	(0.205)	(0.332)	(0.347)	(0.454)
DSHOCK	-0.0427	0.629	-0.180	0.122	0.0658	0.430
	(0.314)	(0.398)	(0.193)	(0.347)	(0.332)	(0.449)
Social Capital and Information						
GROUPM	0.367	0.105	0.295	0.0145	0.997***	0.848
	(0.330)	(0.390)	(0.214)	(0.335)	(0.340)	(0.538)
V_KINSHIP	0.00180	-0.0576	-0.128***	-0.0532	-0.0496	0.0891**
	(0.0366)	(0.0370)	(0.0257)	(0.0386)	(0.0405)	(0.0359)
NV_KINSHIP	-0.00731	0.0942**	0.168***	0.121***	0.102**	-0.247*
	(0.0565)	(0.0438)	(0.0292)	(0.0416)	(0.0444)	(0.134)

EXT	0.188	0.661	-0.613***	-0.572	-0.491	0.497
	(0.354)	(0.416)	(0.237)	(0.478)	(0.374)	(0.573)
CCHANGE	0.216	1.076	1.405***	1.514	1.569**	1.094
	(0.504)	(0.906)	(0.413)	(1.066)	(0.610)	(1.332)
Mundlack fixed effects						
LP_DIS	0.0498	0.117	-0.0852	-0.0889	-0.0235	-0.203*
	(0.0944)	(0.100)	(0.0521)	(0.0946)	(0.0971)	(0.122)
AP_TEENURE	0.962	0.733	0.697*	2.566**	-0.374	2.008
	(0.725)	(0.750)	(0.421)	(1.104)	(0.719)	(1.548)
AMODFER	0.797**	1.454**	0.542**	2.107***	0.789*	2.323***
	(0.402)	(0.609)	(0.263)	(0.539)	(0.456)	(0.732)
AHIGFER	0.0595	1.270	0.0362	1.699***	0.480	1.704*
	(0.617)	(0.806)	(0.376)	(0.642)	(0.636)	(0.928)
AMODSLO	-0.444	-3.073***	-1.478***	-1.398	-1.841**	-2.296*
	(1.321)	(0.795)	(0.559)	(1.001)	(0.884)	(1.339)
AFLASLO	1.318	-3.931***	-1.357**	-0.584	-1.722**	-1.502
	(1.346)	(0.738)	(0.536)	(0.965)	(0.815)	(1.221)
Risk Preference						
EXT_RP	0.201	-1.207*	0.424	-0.0551	0.682	1.785*
	(0.536)	(0.643)	(0.299)	(0.582)	(0.595)	(1.063)
MOD_RP	0.282	-1.695**	0.166	0.534	-0.214	2.754***
	(0.571)	(0.709)	(0.333)	(0.620)	(0.618)	(1.025)
INT_RP	0.140	-0.895*	-0.638**	-0.105	-0.935	1.361
	(0.504)	(0.478)	(0.305)	(0.516)	(0.663)	(1.138)
SLI_RP	0.395	-0.892	1.114***	0.962*	0.853	2.427**
	(0.576)	(0.579)	(0.337)	(0.532)	(0.660)	(1.045)
NEU_RP	0.682	0.126	0.694**	1.165**	1.054*	3.449***
	(0.528)	(0.485)	(0.285)	(0.459)	(0.607)	(0.899)
SAP_Inf_Tra	1.187***	0.516	0.410*	1.828***	0.965**	0.732
	(0.331)	(0.401)	(0.242)	(0.484)	(0.396)	(0.505)
Constant	-5.352***	-6.243***	-2.535**	-12.40***	-5.958***	-12.65***
	(2.008)	(2.413)	(1.110)	(2.778)	(2.084)	(3.616)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	$\chi^2 = 1217.37$		$P > \chi^2 = 0.000$			

Sample size is 1229 plots generated from 421 households and 100 simulation draws were used.***<0.01, **<0.05, *<0.1. Robust standard errors in parenthesis. Fixed effects at plot level are included

5.2 Average treatment effects of SAPs

In this section, we have discussed the economic implication of adoption of SAPs. We specifically answer the following questions. What are the effects of single and combined adoption of SAPs on crop net revenues and consumption expenditure? What are the SAPs packages that yield the highest welfare effects?

Table 4 presents the estimates of the impacts of SAPs on net crop income per acre and on per capita household consumptions. Generally, our results show that most of the SAPs have positive effects on the two welfare outcomes both when they are adopted individually and in combinations, especially on consumption expenditure.

The average adoption effect of only improved maize varieties after controlling for unobserved heterogeneities is about 5.6% on net crop income per acre and about 2.4% on consumption expenditure per capita. This is relatively low as compared to the effects of improved seed varieties found elsewhere. For example Manda, et al., (2015) and Mutenje, et al., (2016) find a 90% and 14.6% impacts of improved maize varieties in Zambia and Malawi, respectively. However, they use maize yield as an indicator, while we use net crop income per acre where we have deducted all the variable costs from the crop revenues. We did not find any significant impact of soil & water conservation ($V_0C_1D_0$) in both net crop income and consumption expenditure when it is adopted in isolation. Cereal-legume diversification leads to around 4% increase in net crop income and about 3.75% in consumption expenditure. Soil & water conservation with improved maize varieties or cereal-legume diversification ($V_1C_1D_0$ / $V_0C_1D_1$) increases consumption expenditure by about 8%.

We also find a positive and significant effect of the SAP package improved maize varieties and cereal-legume diversification. We find the impact to be about 16% in the net crop incomes and about 4.6% in consumption expenditure. We find the highest payoffs both in the net crop income and consumption when all SAPs ($V_1C_1D_1$) are implemented. In quantitative terms, all SAPs adoption leads to about 20% increase in net crop income and around 8% increase in consumption expenditure. This finding is contrary to the few studies elsewhere in Africa. For example, Manda, et al., (2015) and Mutenje, et al., (2016) both find improved maize varieties to have the strongest impact when it is adopted in isolation than when it is implemented with other SAPs. In Ethiopia, Di Falco and Veronesi, (2013), also find higher payoffs when water strategies and changing crops are adopted than when they are implemented comprehensively with changing crop varieties. The difference between our results and former studies could be due to agronomic and location differences. Our study area is known water stress from shortage of enough rains and any agronomic practice implemented can generate higher payoff.

Table 4: Multinomial Endogenous treatment model estimates of SAPs impacts on net crop income and household consumption Expenditure

Variable	**net crop income per acre (ln)**	**consumption expenditure per capita (ln)**
$V_1C_0D_0$	0.0576**	0.0248**
	(-0.0253)	(0.0124)
$V_0C_1D_0$	0.00905	0.0208
	(-0.0321)	(0.0159)
$V_0C_0D_1$	0.0408*	0.0374***
	(-0.0233)	(0.0118)
$V_1C_1D_0$ / $V_0C_1D_1$	0.0157	0.0795***
	(-0.0245)	(0.016)
$V_1C_0D_1$	0.160***	0.0463***
	(-0.0288)	(0.0177)
$V_1C_1D_1$	0.199***	0.0792***
	(-0.0221)	(0.0109)
Selection terms (λ)		
$V_1C_0D_0$	0.110***	0.0499***
	(0.0215)	(0.0156)
$V_0C_1D_0$	0.0294	-0.00148
	(0.0199)	(0.0102)

$V_0C_0D_1$	0.00146	0.0105
	(0.0232)	(0.00924)
$V_1C_1D_0$ / $V_0C_1D_1$	0.0432**	0.0144**
	(0.0199)	(0.00822)
$V_1C_0D_1$	0.0551***	0.01222
	(0.018)	(0.0109)
$V_1C_1D_1$	0.0215*	-0.00587
	(0.0122)	(0.0112)
Lambda	4.912***	7.073***
	(0.469)	(1.127)
Observations	**1229**	**421**

The baseline is farm households that did not adopt any SAP. Sample size is 1229 plots and 421 households and 100 simulation draws were used. ***P<0.01, **P<0.05, *P<0.1. Robust standard errors in parenthesis.

6. Conclusion and Implications

Previous research focuses on mostly single SAP or other innovations adoption and impact to user households. But interestingly, simultaneous adoption and impact of SAPs on households in Africa have received attention recently. In this paper, we have estimated the determinants of different combination of SAPs and their impact on household welfare outcomes. A maximum simulated likelihood estimation of a Multinomial Endogenous Treatment Effect Model (METEM) to account for observable and unobservable heterogeneity that influence SAPs adoption decisions and in turn the outcome variables were estimated on net crop income per acre and per capita consumption expenditure.

The mixed multinomial logit model reveals that the probability of adoption of different combination of SAPs are influenced by observable household characteristics such as education level of the head of the household and family size, plot specific characteristics such as land tenure security, distance of plot from homestead and perceived fertility of plot, social capital and information sources such as membership to group and awareness about climate change and risk preference behaviour of households.

We find generally a positive and significant effect of SAPs except when soil & water conservation is adopted in isolation. The package that contains all three SAPs together (improved maize varieties, soil & water conservation and cereal-legume diversification) generates the highest payoff both in terms of net crop income and consumption expenditure. This has important policy implications. Future interventions that aim to increase agricultural productivity and enhance consumption expenditure should combine improved maize varieties with other best agricultural practices that enhance agronomic practices such as soil & water conservation measures and cereal-legume diversification.

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Appendix

Table 5: Mixed multinomial logit model estimates of adoption of SAPs in Upper East Region of Ghana (baseline category is non-adoption of SAPs)

VARIABLES	(1) $V_1C_0D_0$	(2) $V_0C_1D_0$	(3) $V_0C_0D_1$	(4) $V_1C_1D_0$ $/V_0C_1D_1$	(5) $V_1C_0D_1$	(6) $V_1C_1D_1$
Household Characteristics						
AGE	-0.0435**	-0.0126	-0.00277	-0.0125	-0.0271	-0.0276
	(0.0201)	(0.0216)	(0.0152)	(0.0182)	(0.0180)	(0.0196)
MHEAD	0.686	-0.299	-0.275	-1.355*	0.799	0.888
	(0.888)	(0.773)	(0.520)	(0.698)	(0.743)	(0.849)
FSIZE	0.136	0.0353	-0.0234	0.211**	-0.178*	-0.0748
	(0.110)	(0.115)	(0.0771)	(0.0989)	(0.101)	(0.102)
EDUHEAD	0.258**	0.224	0.297**	0.320**	0.185	0.256*
	(0.127)	(0.155)	(0.120)	(0.137)	(0.131)	(0.132)
Resource Constraints and market access						
DISINPUT	-0.00578	-0.00372	0.00331	-0.00495	0.00149	-0.00354
	(0.00501)	(0.00425)	(0.00276)	(0.00388)	(0.00355)	(0.00373)
CREDIT	-1.054	0.275	-2.466***	-3.163***	0.0635	-1.308**
	(0.678)	(0.618)	(0.576)	(0.754)	(0.564)	(0.630)
Ln_ASSET	0.00565	0.351	0.429*	0.402	0.608*	0.345
	(0.332)	(0.404)	(0.258)	(0.357)	(0.314)	(0.333)
TLU	0.129**	0.101**	0.0491	-0.000424	0.125**	0.165***
	(0.0525)	(0.0471)	(0.0589)	(0.0715)	(0.0505)	(0.0484)
LTCL	-0.696	-0.723	-0.0691	-0.276	-0.0512	0.599
	(0.526)	(0.526)	(0.390)	(0.496)	(0.483)	(0.493)
DSHOCK	-0.0340	1.851**	-0.0371	0.204	0.874*	0.626
	(0.645)	(0.736)	(0.430)	(0.549)	(0.515)	(0.531)
Social Capital and Information						
GROUPM	0.459	-0.528	0.284	0.0454	1.198**	1.387**
	(0.514)	(0.683)	(0.490)	(0.617)	(0.571)	(0.558)
V_KINSHIP	0.0736	0.00741	-0.0831	-0.106*	-0.0896	0.0719
	(0.0575)	(0.0658)	(0.0552)	(0.0628)	(0.0768)	(0.0564)
NV_KINSHIP	-0.0273	0.0808	0.170***	0.174***	0.140**	0.0448
	(0.0733)	(0.0792)	(0.0537)	(0.0628)	(0.0699)	(0.0662)

EXT	0.617	1.639**	-0.226	0.859	0.386	-0.208
	(0.623)	(0.668)	(0.510)	(0.706)	(0.591)	(0.616)
CCHANGE	1.009	0.782	1.448*	1.694	1.038	1.566
	(0.851)	(0.939)	(0.810)	(1.394)	(0.929)	(1.242)
Mundlack fixed effects						
LP_DIS	0.267	0.179	-0.0881	0.153	0.124	0.0135
	(0.164)	(0.172)	(0.108)	(0.137)	(0.144)	(0.137)
AP_TEENURE	0.794	1.715	2.433**	4.061**	1.042	1.719
	(1.005)	(1.314)	(0.983)	(1.583)	(1.080)	(1.112)
AMODFER	0.654	1.933**	0.751	1.429**	1.242*	2.442***
	(0.675)	(0.924)	(0.560)	(0.672)	(0.669)	(0.786)
AHIGFER	-0.981	0.142	0.0445	1.469*	0.0872	2.054**
	(0.936)	(1.589)	(0.850)	(0.889)	(1.131)	(0.980)
AMODSLO	2.073	-3.340**	-0.117	-1.507	-0.456	-2.947**
	(3.982)	(1.434)	(1.274)	(1.416)	(2.087)	(1.422)
AFLASLO	4.939	-5.020***	0.352	-1.258	-0.433	-2.909**
	(3.982)	(1.407)	(1.208)	(1.360)	(2.044)	(1.386)
Risk Preference						
EXT_RP	-1.315	-0.635	0.437	-0.190	0.119	2.109***
	(0.938)	(0.860)	(0.584)	(0.760)	(0.788)	(0.816)
MOD_RP	0.337	-1.976	-0.0419	0.360	-1.111	1.643*
	(0.888)	(1.206)	(0.778)	(0.964)	(0.965)	(0.923)
INT_RP	-0.583	0.0916	-0.350	-0.133	-0.604	1.102
	(0.860)	(0.848)	(0.595)	(0.839)	(0.809)	(0.931)
SLI_RP	1.881*	0.879	2.507***	2.397**	1.780*	3.105***
	(1.047)	(1.034)	(0.926)	(0.981)	(1.021)	(1.129)
NEU_RP	1.492	1.525	1.457**	2.132**	1.773**	3.908***
	(0.945)	(1.047)	(0.692)	(0.856)	(0.878)	(0.918)
SAP_Inf_Tra	2.831***	1.521**	0.555	1.126	1.901***	2.138***
	(0.671)	(0.678)	(0.516)	(0.724)	(0.571)	(0.636)
Constant	-8.014	-7.539*	-7.977***	-13.01***	-9.797***	-11.33***
	(5.021)	(4.315)	(2.517)	(3.925)	(3.484)	(3.345)
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	$\chi^2 =$ 1278.20	$P > \chi^2 = 0.000$				

Sample size is 421 households and 100 simulation draws were used.***<0.01, **<0.05, *<0.1. Robust standard errors in parenthesis. Fixed effects at plot level are included

Table 6: Test on the validity of instrument

VARIABLES	(1) net crop income per acre (ln)	(2) consumption expenditure per capita (ln)
AGE	-0.00265	-0.00461
	(-0.00331)	(-0.00311)
MHEAD	0.0312	-0.123
	(-0.121)	(-0.116)
FSIZE	0.0469***	-0.0663***
	(-0.0171)	(-0.02)
EDUHEAD	-0.00874	0.0265
	(-0.019)	(-0.0325)
DISINPUT	-0.000732	0.000251
	(-0.000615)	(-0.000695)
CREDIT	0.000998	0.138
	(-0.105)	(-0.109)
Ln_ASSET	0.00456	0.0758
	(-0.0618)	(-0.0678)
TLU	0.00762	-0.00199
	(-0.0086)	(-0.0151)
LTCL	-0.299***	0.00399
	(-0.105)	(-0.107)
DSHOCK	0.102	-0.308***
	(-0.0926)	(-0.103)
GROUPM	-0.00922	-0.0369
	(-0.107)	(-0.117)
V_KINSHIP	-0.00348	0.0227*
	(-0.00991)	(-0.013)
NV_KINSHIP	-0.0095	-0.00188
	(-0.0121)	(-0.0172)

EXT	0.119	0.0764
	(-0.105)	(-0.0947)
CCHANGE	0.0246	0.185
	(-0.153)	(-0.146)
LP_DIS	0.0192	0.0460*
	(-0.0261)	(-0.0245)
AP_TEENURE	-0.386*	-0.156
	(-0.205)	(-0.181)
AMODFER	0.115	-0.0596
	(-0.12)	(-0.11)
AHIGFER	0.205	-0.07
	(-0.19)	(-0.19)
AMODSLO	0.133	0.318
	(-0.299)	(-0.234)
AFLASLO	0.0725	0.325
	(-0.297)	(-0.233)
EXT_RP	-0.184	-0.0686
	(-0.136)	(-0.121)
MOD_RP	-0.224	0.111
	(-0.145)	(-0.147)
INT_RP	-0.176	-0.128
	(-0.133)	(-0.131)
SLI_RP	-0.0315	-0.083
	(-0.166)	(-0.244)
NEU_RP	0.136	-0.0628
	(-0.15)	(-0.17)
B	-0.0525	0.0444
	(-0.127)	(-0.143)
BW	0.0438	-0.592***
	(-0.134)	(-0.167)
KNE	0.039	-0.451***
	(-0.161)	(-0.152)
SAP_Inf_Tra	**-0.1**	**0.0252**
	(-0.108)	**(-0.0997)**
Constant	5.747***	6.769***
	(-0.555)	(-0.532)
Observations	474	96
R-squared	0.081	0.599

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1