Role of Social Capital on Uptake of Sustainable Agricultural Intensification Practices' Combinations

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Abstract
Smallholder farmers in sub-Saharan Africa are faced with many challenges in the production of maize and legumes. Some of the challenges include soil mining, drought, soil erosion, input acquisition among others. These challenges cannot be alleviated with the adoption of a single agricultural practice but a bundle of combination. There was need, therefore, to evaluate if social capital among other factors influences adoption of the different combination of the six Sustainable Agricultural Intensification Practices among smallholder maize-legume systems in Kenya. The study used secondary data from Adoption Pathway project panel dataset collected from Bungoma, Siaya, Meru, Tharaka Nithi and Embu counties, in three waves: covering 613 households in the baseline, 535 in the midline and 495 in the end line was used in the analysis. Eighteen possible combinations adopted by smallholder farmers, a Principal Component Analysis was used to reduces data dimensionality, such that Seven possible clusters were formed that were homogeneous within. An index of the different combinations in the cluster was then formed for each household. Using STATA software, a Seemingly Unrelated Regression model was used in the analysis of the seven equations against a set of dependent variables, among them social capital. The findings of the study showered that social capital is not significant in explaining adoption of different combinations of SAIPs that a household adopted except for cognitive social capital and participation level in group institutions where the household was a member. Other factors that influenced adoption of combination of SAIPs included age of the household head, received information about SAIP and input markets, amount of money that a household got as income and that which they saved. Additionally, the spatial distance of the farming plot measured as the number of walking minutes from the household homestead and the number of years one has been living in the village practicing maize-legume production also significantly influenced the combinations of the SAIPs that a household adopted. Policy interventions should encourage and promote better access to information and encourage participation in group institutions.
Keywords: Principal Component Analysis, Clusters, Seemingly Unrelated Regression

1 Introduction

The rapid population rise of the world especially in the less developed countries like Sub-Saharan Africa are posing a challenge of feeding everyone. This is deepened by virtue that there is declining soil fertility, soil mining, environmental degradation, and global climate change while arable land is shrinking or remains constant. Sustainable Agricultural Intensification Practices (SAIPs) are considered as the remedy to this challenge and have been promoted widely by the government, non-governmental organization, and scientists in Kenya, but their uptake has remained low among smallholder maize-legume farmers, hence need to explore whether social capital promotes SAIPs uptake. The study was also motivated by the fact that, there are little empirical studies that explore the interrelationship between the social capital, SAIPs uptake and of context-specific food security challenge among smallholder maize-legume farmers in Kenya. The study aims at filling this gap by identifying social capital forms among smallholder maize-legume farmers and whether they promote SAIPs combinations uptake and ultimately improve the productivity of maize and legumes in Kenya (Baumgart-Getz, Floress, and Linda, 2012).

2 Literature Review

Smallholder maize-legume farmers in Kenya are facing multiple challenges in production, which calls for multiple approaches rather than the adoption of a single SAIP (Kassie, Jaleta, Shiferaw, Mmbando, and Muricho, 2012). The use of SAIPs has received a lot of emphasis due to its environmentally friendly approach in the recent past. However, the uptake has remained low (Nato, Shauri, and Kadere, 2016). Since the SAIPs can improve production, there is need to know the factors that influence their rapid uptake. Higher agricultural production must be realized to cater for the rapidly rising population in Kenya and across the globe (Melorose, Perroy, and Careas, 2015).

Smallholder maize-legume farmers produce the highest proportion of the cereal requirements in the country (Kirimi *et al.*, 2011), hence need to create awareness on the SAIPs combination (Sidique and Hadi, 2016). Adoption of agricultural practices is attributed to networks that households has and whom they trust to get reliable information from (Macharia, 2012). Agricultural shows and access to finances were also found to be significant by (Nkegbe and Shankar, 2014). Arslan, McCarthy, Lipper, Asfaw, and Cattaneo (2014)found extension services and household unobservable such as openness to innovations to be significant in the adoption of agricultural practices. Participation in collective action and membership to institutions were also significant in a study by Willy and Holm-Müller (2013). Other factors which influence adoption of agricultural technologies or practices include the age of the household head maker or head, sources of information and credit availability (Challa and Tilahun, 2014; Cochrane, 2014; Ogutu and Obare, 2015). However, Arslan *et al.,* (2014) did not find age to be significant in explaining adoption. Ainembabazi and Mugisha (2014) also argued that stock of education is not as vital as years of experience in an agricultural setting. This study considered a combination of different SAIPs unlike others earlier studies which handled the adoption of a single practice. The motivation was that smallholder farmers adopt different SAIPs in combination, as opposed to one by one (Teklewold, Kassie, and Shiferaw, 2012). The reason behind the adoption of unlike groups of SAIPs is that different farmers face diverse challenges in production. The challenges are also numerous in nature that require multiple SAIPs to address them, hence SAIP combinations.

Social capital has the capacity of improving resource management for collective action. It can also improve access to resources through linkages to the government, non-governmental as well as other relevant institutions (Gulati, 1998; Krishna and Uphoff, 1999; Grootaert and Van Bastelaer, 2000; Narayan and Cassidy, 2001; Tscharntke *et al.,* 2012). This study followed Grootaert and Van Bastelaer, (2001) approach of having social capital measured in four different forms at a household level. They included group membership; participation in decisions making in groups; Networks density and finally the cognitive aspect of social capital, which highlights who a household can trust. Network density involves the number of people (friends, relatives, and non-relatives). They could be within or outside the village. These are people whom a household can rely in times of need. Membership and participation involves the number of institutional groups a household is a member and the level of participation in each one of them (Pratiwi and Suzuki, 2017).

Majority of these reviewed studies based their conclusions on single agricultural practices, using binary choices. Samples that they used were small, and most of them were cross-sectional except that of Teklewold *et al.* (2013) which was a panel in kind and dealt with multiple SAIPs adoptions in Ethiopia. This objective handled the above weaknesses and considered the fact SAIPs could be substitutes or compliments of each other. The idea of combining the SAIPs using the PCA approach was addressing the impression that household maize-legume producers adopted the SAIPs in combination and not in piecemeal.

3 Area description

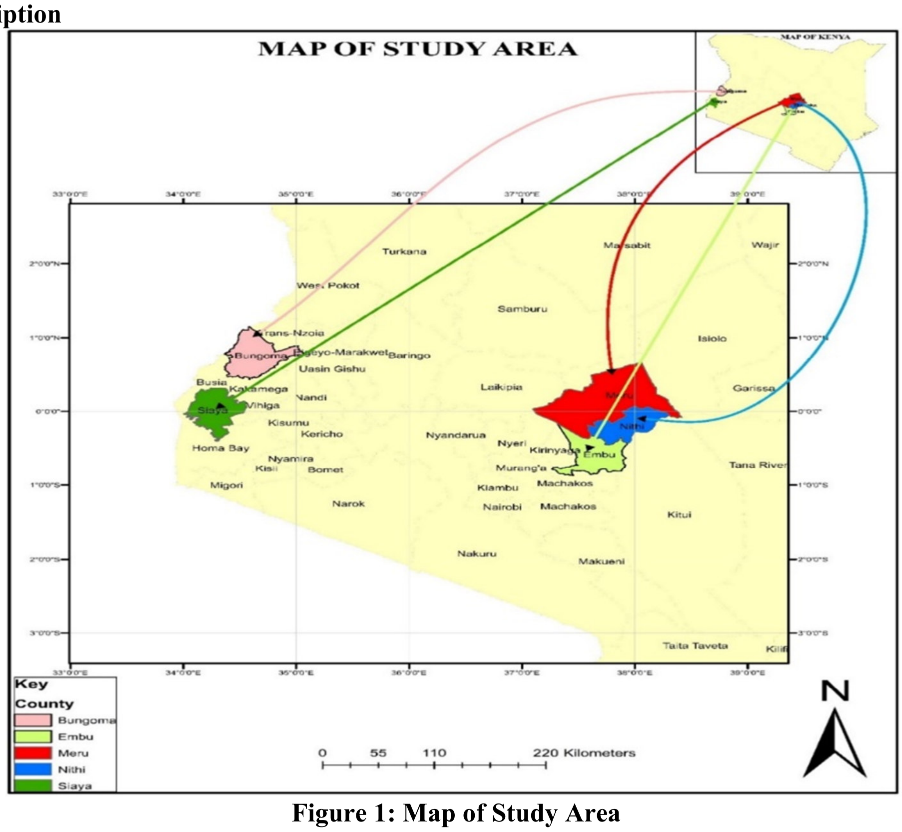

Figure 1: Map of Study Area

Source: Virtual Kenya and Google Earth Pro. 2015

This study used AP panel data, from Siaya and Bungoma in the Western region and Embu, Meru and

Tharaka Nithi counties in the Eastern region. Figure 1.

Embu County covers an area of 2,818 km^2 and borders Tharaka Nithi to the North. Embu County covers 2,818 km^2. It has a population density of 183/km^2 and borders, Kitui to the East, Machakos to the south, Muranga to the South-West, Kirinyaga to the West and Meru to the North-West. (Kenya Bureau of Statistics (GoK, 2009). The county is characterized a bimodal rain pattern, with the peak rainfall falling between March and June (GoK, 2009).

Meru County covers an area of 6,936.9 km^2 with a total population of about 1,356,000 in 320,616 households. The population density is 200/km^2. Temperatures range between a minimum of 16°C to a maximum of 23°C. The county receives rainfall of between 500mm and 2600mm per annum. The main agricultural activities include dairy, French beans, yam, cassava, pumpkin, millet, and sorghum production. The poverty levels are reported to be 41% (Meru Central) and 47.3% (Meru North) (GoK, 2009).

Siaya County has a total population of 842,304, with 199,034 households. The population density is 332/km^2 per square km with 57.9% of the population living below the poverty line. The county receives an annual rainfall of between 1,170 and 1,450mm with a mean annual temperature of 21.75°C and a range of 15°C and 30°C. Other than agricultural land, the area has other vital resources such as fisheries, indigenous forests, rivers, and timber. The main economic activities include subsistence farming, livestock keeping, fishing, rice farming and small-scale trading (GoK, 2009).

Bungoma County has a population of 1,375,000 with an area of about 3,032km^2 and a population density of about 454/Km^2. The county's economy is primarily agricultural, with sugarcane and maize as the main subsectors. The county receives high amounts of rainfall almost throughout the year and hosts several large rivers, which are used for small-scale irrigation. The temperatures range from a minimum of between 15 - 20°C. With the agricultural production of sugarcane, coffee, maize, milk, tobacco, bananas, and sweet potatoes. Poverty level stands at 53% below poverty line(GoK, 2009).

Tharaka Nithi has a population of about 356,000 consisting of 88,800 households. It covers an area of 2,639 km^2, with temperatures range of 11°C to 25.9°C. It receives rainfall of between 200 - 800mm per annum. The population density is 138/km^2, with 65% of the population living below the poverty line. The county has a lot of resources including arable land, sand quarries, forests, and wildlife. The major income earning activity in the county include farming, pastoralism, gemstone mining, and harvesting, and stone quarrying (GoK, 2009).

The conditions in these five counties provide a suitable climatic condition that is suitable for maize and legume production. Despite ample rainfall and maize-legume production potential of these counties, they still record high levels of their population living below the poverty line. There is need therefore to help advance the productivity of each household through the adoption of SAIPs and general use of land. This will to help improve real income, food sufficiency, nutrition and reduce poverty within these counties and the country at large (GoK, 2010).

4 Sampling and Data Collection

4.1 Sampling Design

Table 1: Sampling and sample size

County	Baseline 2011	AP Midline	Attrition (%)	End line (2015)	Attrition (%)
Bungoma	150	137	9	120	20
Embu	111	93	16	85	23
Tharaka-Nithi	101	81	20	81	20
Meru	102	81	21	67	34
Siaya	149	143	4	142	5
Total	613	535	13	495	19

A multi-stage sampling procedure was employed to select lower levels sampling clusters; divisions, locations, sub-locations, and villages, from where households were identified, during the baseline survey of the predecessor project, SIMLESA. In 2013, household sampled were 535 out of the 613 that had been surveyed during the SIMLESA baseline survey in 2011, this was an attrition rate of 13%. A higher attrition in Eastern Kenya counties of Meru, Tharaka Nithi and Embu was recorded, compared to western Kenya counties. In 2015, 495 households were surveyed, suggesting an attrition rate of 19%. Again, relatively higher attrition rates were reported in eastern counties with Meru reporting a rate of 34%. The various levels of attrition were attributed to, among others, households' outmigration to far distant villages, while other villages had been dissolved, as well as movement from the rural to urban areas in search of work out of agriculture; deceased respondents; and respondents being outrightly unavailable. Table 2 shows the sample size across the panel with respective attrition rates.

4.2 Data Collection Method and Management

The formal survey involved recruiting and training of enumerators who administered the structured questionnaires. Data from these smallholder maize farmers were made up of basic household characteristics such as family size, education levels of household head, occupation, farmer groups/associations, income diversification, crop inventory, access to farm inputs and markets access. The natural physical characteristics of the study area like the state of infrastructure and approximation of the distances were captured through observation method. Other information collected included: The household assets ownership was captured by inquiring the number of livestock and non-livestock asset ownership. The income level of the household was addressed by inquiring the amount of saving that the household made, income generating activities carried out by the household and, credit access level status of the household. How readily a household gets information was pegged on how frequent one could access extension services. At the individual household level for the disaggregated case, the questionnaire addressed issues like membership to farmer groups or institutions, participation level of the group or institutions where the household was a member and network density. The questionnaire also addresses the maize-legume variety used by households, their perception of climate change and decision making on key aspects of the livelihood of the household among others.

The data were cleaned and analyzed using Statistical Package for Social Sciences (SPSS) and STATA statistical software.

5 Econometric Techniques and Model Specifications

Analysis was done using a Seemingly Unrelated Regression (SUR) model. SUR model was preferred over other models because of its potential of handling different continuous dependent variable against a set of explanatory variables where the error term has a likelihood of possible correlation (Zellner, 1962; Henningsen, 2012). The model was estimated using equation 1 below.

$$Y_{ijt} = x_{ijt}^{T}\beta_t + \varepsilon_{it} \qquad 1$$

where *j = 1, 2, …, m* represented the number of equations and Y_{ij} is the index associated with each equation for a given combination of SAIPs in a cluster in different equations for different households.

Following the innovative approach of Birhanu *et al.* (2011) and Cavatassi, Davis, and Lipper (2004), An index of the SAIPs various combinations were created as per equation 2 below.

$$Y_{ji} = \sum_{l=1}^{p}\left[f_{ij}\left(\frac{l_{ji} - \bar{l}_j}{s_j}\right)\right] \qquad 2$$

where Y_j is the j^{th} combination of SAIPs, f_{ij} is the weight of the associated household *i* using j^{th} combination from the PCA model. l_{ji} is the land where i^{th} household is using j^{th} SAIP combination while $\overline{l_j}$ and s_j is the mean land size and standard deviation where the j^{th} combination was applied. Since the study used panel dataset from three rounds, then, to incorporate the time factor and variability of the index over time, the data were pooled for the three rounds and estimated the principal component over the combined data (Demeke, Keil and Zeller, 2011). The weight that resulted from the combined data was applied to the variable values of each round of the data to construct a continuous variable index for the different combinations using equation 5-3 (Cavatassi, Davis and Lipper, 2004).

$$Y_{ijt} = \sum_{l=1}^{p}\left[F_{ijt}\left(\frac{l_{ijt} - \bar{l}_{jt}}{s_{jt}}\right)\right] \qquad 3$$

The variables were as defined previously defined in equation 5-2, with *t* representing time factor in equation 3. The created index was used as the dependent variable and a regression run against the explanatory variables using the Seemingly Unrelated Regression (SUR) model in equation 1.

6 Results and Discussions

6.1 Descriptive Statistics

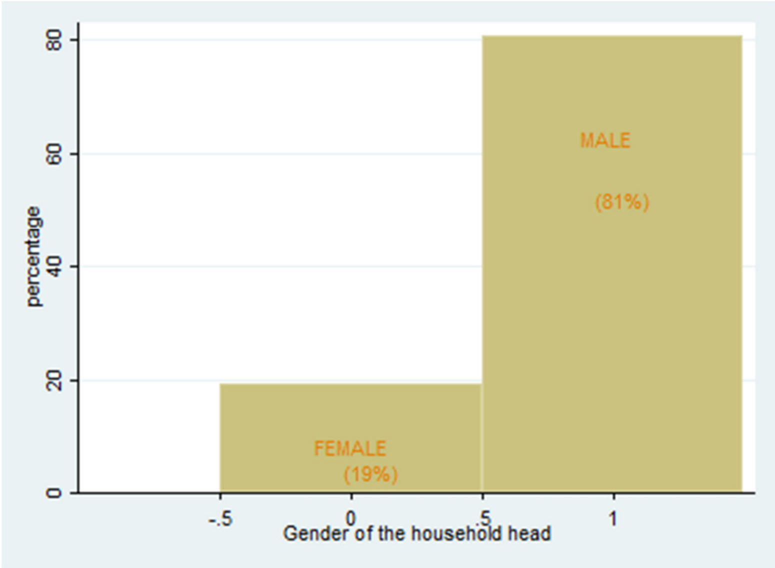

Figure 2: Gender of the household head

Table 3: Showing Household Gender Headship per County

County	Baseline		Midline		Endline	
	Female	Male	Female	Male	Female	Male
Bungoma	19.0	125.0	21.0	105.0	12.0	99.0
Tharaka	14.0	89.0	12.0	74.0	10.0	66.0
Embu	24.0	89.0	15.0	74.0	21.0	67.0
Meru	10.0	65.0	15.0	56.0	3.0	68.0
Siaya	40.0	113.0	46.0	102.0	36.0	89.0
Total	**107.0**	**481.0**	**109.0**	**411.0**	**82.0**	**389.0**
%gndr	**18.2**	**81.8**	**21.0**	**79.0**	**17.4**	**82.6**
CHI-2(n)	X^2 *(4)* = 12.3*		X^2 *(4)* = 14.0*		X^2 *(4)* = 26.7***	

X^2 *(4)* = 43.8***

The result showed that 19% of the respondent household was headed by the female while counterpart males headed 81% Figure 2. More females headed a household in Siaya County of the Western region while Meru of the Eastern region recorded the least female headships shown in Table 3. The Pearson chi-square test showed significant differences in household headship within the counties across the panel. On average, there are significant differences in household headship within the counties and across the panel at 10% level of significance. Female household headship remained low across the panel. More significant differences in gender headship were realized in the end line at 10% significance. These results implied that there were no efforts in empowering women to take up headship roles or the men who were away working could have come back home and taken all the household headship roles.

Table 4: Table showing percentage respondents for those who received information about SAIPs

	Bungoma	TharakaNithi	Embu	Meru	Siaya
BASELINE					
Yes	31.9	29.7	31.5	36.6	31.0
No	68.1	70.3	68.5	63.4	69.0
MIDLINE					
Yes	34.4	29.5	30.6	29.4	33.1
No	65.6	70.5	69.4	70.6	66.9
ENDLINE					
Yes	31.1	30.8	23.5	26.9	29.4
No	68.9	69.2	76.5	73.1	70.6

The number of households that received information across the panel was low averaging at 30% **Table 4**. There is no county that had a significant number of household which got relevant information in the production of maize and legumes. The Pearson Chi-square was not significant across the counties and panel. There is need therefore to invoke those responsible to improve the dissemination of information on the appropriate combinations that can be applied to obtain optimal yield. Similarly, awareness about input prices had even fewer household which received information. It is imperative for farmers to have knowledge about the market prices of farm inputs. This can help smallholder farmers in planning their expenditures in farming operations. Different dealers or agro-vets sell same inputs at different prices due to price discrimination. A rational farmer who is out to reduce the cost of production of the maize-legume system could wish to know where prices are low. On the other hand, different brands of day seeds of maize and legumes could be available at different prices and potential expected yield. This makes knowledge about the prices of inputs crucial to a household, in the calculation of cost and revenue streams. Any person involved in the production must know the prices of inputs because that is where the cost of production starts to pile up.

Table 5: Table showing percentage respondents for those who received information about input prices

	Bungoma	Tharaka Nithi	Embu	Meru	Siaya
BASELINE					
Yes	16.2	13.7	6.1	18.4	10.1
No	83.8	86.3	93.9	81.6	89.9
MIDLINE					
Yes	16.3	19.2	23.3	17.1	18.7
No	83.7	80.8	76.7	82.9	81.3
ENDLINE					
Yes	10.2	27.3	20.5	21.6	14.5
No	89.8	72.7	79.5	78.4	85.5

The results in **Table 5** indicated that Bungoma had households who received information drop to 10% in the end line from 16% in the baseline. Other counties generally had an improvement in disseminating information to households across the panel, with Embu and Tharaka Nithi recording the highest improvement change from 6% to 23% and 14% to 27% respectively. At least, agents involved in creating awareness and training tried to reach many households after the baseline. However, more needs to be done to reach more households.

6.2 Description of Variables used in the Regression

The results of **Table 6** showed the summary of the variables that were included in the regression and their description. The average age of the household head was 52 years and the natural logarithm of the total amount of money a household saved, and the amount they got as income was 7.4 and 9.3 respectively across the panel. The trend for saving and income was relatively higher in the beginning, with a slight drop in the midline and a rise in the end line. Plots, where most of the households were cultivating, were generally near with an average walking distance of 10 minutes. However, some household had to walk for over 5 hours to the plots, and this are probably rented in plots. The time a household member had to travel influenced the bulk inputs like manure and fertilizer. This could require additional cost for transportation, raising the cost of production. On average households had lived in the village for 30 years. This is a relatively long period that people have had an idea of the production patterns and the possible SAIPs combinations for optimal yield. However, it was noted that some household had just migrated there and did not have any experience living in the village hence learning from others and extension services were crucial.

Even though information is vital in the production of goods and services, a few households received information about input prices and SAIPs combination. This was evidenced by a low percentage showing those who received information averaging at 31.2% for information about SAIPs and 16.2% for information about input prices. This implied that smallholder farmers do not receive adequate information to help them prepare for farming activities. However, a greater percentage of household received training from government extension officers relative to other information sources. It was noted that the extension visits were of a range of issues and did not particularly handle the SAIPs aspect particularly but a range of issues including livestock and general diseases. The training was done in Barazas and groups and therefore the farmers did not get that physical touch with officers and engage on a personal level. Follow-up was also minimal, evidenced by the frequency of visits or training hence may be difficult to track and know if a given aspect of the training was taken seriously.

Table 6: Data Definition and Descriptive Statistics

			Baseline		Midline		C	
Variable	Description	Measurement	Mean	Std	Mean	Std	mean	std
Agehh	The age of the household head	Age in years of the household head	51.60	14.20	53.50	14.40	52.00	14.20
lTOTAL_sav	Log of money a hh saved	Natural logarithm of money	7.40	3.90	7.30	4.00	7.60	4.00
lTOTAL_incom	Log of money hh get as income	Natural log of money	9.60	3.80	9.20	4.10	9.30	4.10
avrg_plot_dist	Average plot distance from home	Measured in walking minutes	10.00	16.40	7.80	19.70	6.00	14.00
yrs_lvd_vlg	Number of years hh has lived in the village	Years	30.00	19.10	30.10	14.30	29.60	18.70
network_density	The number of people a hh knows and can rely on for help in times of need	A discrete number of people	48.00	49.00	48.00	41.00	44.00	38.00
prtcpn_score	The score of participation in group in which hh are members	Score	0.49	0.41	0.50	0.43	0.50	0.41
Cogniscore	The score of trust of a household	Score	7.91	2.95	7.80	2.73	7.88	2.82
mbrshp_score	The score of membership in which a hh is a member	Score	1.31	0.90	1.41	1.00	1.40	0.93
	Dummy variables (represented as a percentage of the respondent)		**Yes**	**No**	**Yes**	**No**	**Yes**	**No**
got_ext	Household got an extension from government and other sources.	Dummy: 1- Yes, 0-No	66.90	33.10	62.80	37.20	66.60	33.40
info_inpt_mkt_price	If hh had information about input prices	Dummy: 1- Yes, 0-No	12.30	87.70	19.20	80.80	18.90	81.10
recvd_info_saips	If a hh received information about SAIPs	Dummy: 1- Yes, 0-No	32.50	67.50	32.20	67.80	28.40	71.60

A social capital factor was captured in four aspects. They included network density, group membership, cognitive score, membership score, and participation in groups in which a household was a member (Krishna and Uphoff, 1999; Grootaert and Van Bastelaer, 2001; (Mwakubo, Obare, Omiti, and Muhammed, 2005). Network density involved friends, relatives and those in leadership positions in and out of the village that one can call on to get help from. The help could be in form of seed sharing, food, financial and advice. It is important to note that a household could also learn from these people upon visiting. Some households had over 200 people whom they could rely on while others have as few as 10 people. It was important to know the level of trust a household has on other people in the society. This will determine where they make savings to buy inputs; the sellers in agro-vets from where they could get inputs, and advice as well as from whom they can get reliable information (Bjomskov and Svendsen, 2000; Birhanu *et al.,* 2011; Rotaru *et al.,* 2012; Ivory *et al.,* 2012). Membership in a diverse group also could broaden the chances of getting multiple aids, interacting with many people on possible combinations, and learn from each other with ease. Finally, participation in groups where they were members could increase chances of getting loans be able to organize for inputs.

The results of **Table 7** and the **table in Appendix 1** represented the Principal Component Analysis (PCA) approach, which was used to cluster the various combinations that were adopted in this study. PCA helps to reduce data dimensionality without loss of information (Reise, Waller, and Comrey, 2000). It is a better approach compared to conventional grouping practice which may make it difficult to conclude about a given group. The PCA ran a regression of the various combinations and obtained different loading factors associated with each combination (Svendsen, 2000; Birhanu *et al.,* 2011). Components that had a value greater than one were chosen to form combinations. The components were rotated to obtain orthogonal varimax(Glendon and Ryan, 1998). The rotation was to help obtain combinations which are highly correlated with each component for easy interpretation and generalization (Goswami, Biswas, Basu, and Viswavidyalaya, 2012). From the rotated varimax, different combinations used by the households in different plots were identified and put in different heterogeneous principal clusters by use of principal component analysis which is homogeneous within (Chatterjee, Goswami, and Bandyopadhyay, 2015)

6.3 Post-estimation Diagnostics

Diagnostic check was done before estimating the SUR model. To test for multicollinearity, the highest variance inflation factor (VIF) was 1.29 for the age of the household head, which was within the acceptable range. In testing for heteroscedasticity, a Breusch - Pagan test was carried out (Gujarati and Porter, 2009). The result rejected the null hypothesis of homoscedasticity and confirmed that there was heteroscedasticity. However, this is not a big problem as per Gujarati and Porter (2009) which can render the model null and the fact that panel data itself is out to solve the problem. The Woodridge test of autocorrelation in panel data failed to reject the null hypothesis of no autocorrelation of the error term. Equally the Cumby-Huizinga test of autocorrelation confirmed that the data did not have a serial correlation. The above tests confirmed that the regression results would produce unbiased, efficient and least variance estimates. The Kaiser- Meyer- Olkin measure of sampling adequacy was 0.6134 which was above the minimum requirement of 0.50, hence the result from PCA was reliable, and it was worthy to conduct a PCA analysis to help in clustering. The Orthogonal Varimax (Kaiser off) Rho = 0.5537 which is above the acceptable minimum of 0.5. PCA was conducted to help in data reduction through clustering to get combinations that were homogeneous within and heterogeneous in the next cluster. All the above tests cumulatively assured unbiased estimates from the regression.

Before analysis, the possible 18 combinations of SAIPs were reduced to seven components by PCA data reduction technique that formed clusters that were homogeneous within and heterogeneous in different clusters (Smith, 2002; Walde, 2014) shown in **Table 9** and **Table 10.** The PCA reduces data dimensionality to a manageable level without loss of information (Reise, Waller and Comrey, 2000). This reduced the equations to be estimated to a manageable number of 7 as shown in Table 5-V. The selection of the 7 combinations was based on the eigenvalues chosen that had a value greater than 1. The seven clusters formed each of which had a different combination of the SAIPs is as represented as components in **Table 8.**

6.4 Econometric Results

The econometric results of the SUR model were represented in **Table 11** and it showed that **Cognscore** (Cognitive social capital) which comprised of who the household trusts were significant in improving uptake of SAIPs combinations in cluster 3, 4, 5 and 6. The people a household trust improves transactions, reliability, and ease of taking risks. Households that trust extension officers are more likely to take up the advice given by them and put it into practice. Similarly, they can take up their money and make savings in various groups without fear of fraudulent behaviors among the leaders or the lenders. They can adapt and continue using combinations that the people they trust advice and therefore more likely to realize higher adoption rate and yield. The study found out that those whose level of trust is relatively higher, and one can rely on the advice they get from them are more likely to adopt combinations in cluster 3, 4, 5 and 6. The combinations in this clusters generally showed how households combine variety and conservation agricultural practices to realize higher yield. That is manure, intercropping, minimum tillage, and rotation. These practices have an advantage that they are environmentally friendly, and they increase the output level of the farmer. Empirically, increase in one unit in the score of cognitive, will improve uptake of combinations in: cluster 3 by 0.182 units at 5% level of significance; cluster 4 by 0.018 units at 1% level of significance; cluster 5 by 0.012 units at 5% level of significance and cluster 6 by 0.022 units at 1% level of significance. Conversely, Nato *et al.* (2016) did not find social trust form of social capital to be significant in explaining adoption decision, citing that strong social trust leads to reluctance in adoption until others have significantly adopted.

Table 7: Table showing PCA Estimation; Rotation (unrotated = principal)

Components	Eigenvalues	Difference	Proportion	Cumulative
Comp1	2.193170	0.343849	0.1218	0.1218
Comp2	1.849320	0.500198	0.1027	0.2246
Comp3	1.349130	0.049361	0.0750	0.2995
Comp4	1.299760	0.130551	0.0722	0.3717
Comp5	1.169210	0.066572	0.0650	0.4367
Comp6	1.102640	0.099333	0.0613	0.4980
Comp7	1.003310	0.007395	0.0557	0.5537
Comp8	0.995912	0.036584	0.0553	0.6090
Comp9	0.959328	0.030797	0.0533	0.6623
Comp10	0.928530	0.051007	0.0516	0.7139
Comp11	0.877523	0.087142	0.0488	0.7627
Comp12	0.790381	0.088364	0.0439	0.8066
Comp13	0.702017	0.025043	0.0390	0.8456
Comp14	0.676974	0.018447	0.0376	0.8832
Comp15	0.658526	0.044164	0.0366	0.9198
Comp16	0.614362	0.169086	0.0341	0.9539
Comp17	0.445275	0.060650	0.0247	0.9786
Comp18	0.384625		0.0214	1.0000

Table 8: PCA components with Eigenvalues greater than one rotated orthogonal varimax

Components	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.98247	0.0701775	0.1101	0.1101
Comp2	1.91230	0.5781040	0.1062	0.2164
Comp3	1.33419	0.0171671	0.0741	0.2905
Comp4	1.31703	0.1091720	0.0732	0.3637
Comp5	1.20785	0.0177580	0.0671	0.4308
Comp6	1.19010	0.1674900	0.0661	0.4969
Comp7	1.02261		0.0568	0.5537

Table 9: Component combinations

Compo1	Compo2	Compo3	Comp4	Compo5	Comp6	Compo7
Vrm	Vfi	Vm	Vi	Vf	Vr	v
Vrmf	Vmfi	Vmt	Vit	Vmi	Vri	
Vrmfi	Vrfi			Vt	Vrmi	

Table 10: Table showing clusters of SAIPs from which an index was formed for different combinations

Clusters and combinations	Description of the combinations
Cluster	
Vrm	Seed variety+ crop rotation + manure application
Vrmf	Seed Variety+ crop rotation + manure application +fertilizer application
Vrmfi	Seed Variety+ crop rotation + manure application +fertilizer application + intercropping maize and legumes
Cluster 2	
Vfi	Seed Variety + fertilizer application +intercropping maize and legumes
Vmfi	Seed Variety + manure application + fertilizer application +intercropping maize and legumes
Vrfi	Seed Variety + rotation+ fertilizer application +intercropping maize and legumes
Cluster 3	
Vm	Seed Variety + manure application
Vmt	Seed Variety + manure application + minimum tillage
Cluster 4	
Vi	Seed Variety+ intercropping maize and legumes
Vit	Seed Variety+ intercropping maize and legumes +minimum tillage
Cluster 5	
Vf	Seed Variety+ fertilizer application
Vt	Seed Variety+ minimum tillage
Vmi	Seed Variety + manure application + intercropping maize and legumes
Cluster 6	
Vr	Seed Variety + crop rotation
Vri	Seed Variety + crop rotation + intercropping maize and legumes
Vrmi	Seed Variety + crop rotation + manure application + intercropping maize and legumes
Cluster 7	
V	Seed Variety

Table 11: Seemingly Unrelated Regression Model Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	**factor_1**	**factor_2**	**factor_3**	**factor_4**	**factor_5**	**factor_6**	**factor_7**
network_density	-0.00025	1.96e-05	0.000232	-0.000265	0.000914	0.000446	-0.000302
	(0.0003)	(0.000364)	(0.000626)	(0.000725)	(0.00152)	(0.000906)	(0.00175)
prtcpn_score	-0.02540	0.00838	0.0917	0.167**	0.109	0.101	0.381**
	(0.0311)	(0.0331)	(0.0570)	(0.0660)	(0.138)	(0.0825)	(0.159)
Cognscore	0.00115	0.00197	0.0182**	0.0179*	0.0415**	0.0223*	0.0313
	(0.0044)	(0.00467)	(0.00804)	(0.00931)	(0.0195)	(0.0116)	(0.0225)
mbrshp_score	0.01430	0.00960	-0.00538	-0.0314	0.0539	0.0123	-0.0217
	(0.0141)	(0.0150)	(0.0258)	(0.0299)	(0.0625)	(0.0373)	(0.0721)
Agehh	-0.00092	-0.00119	-0.00119	0.000186	-0.00217	-0.00475**	-0.00142
	(0.0009)	(0.000931)	(0.00160)	(0.00186)	(0.00388)	(0.00232)	(0.00448)
recvd_info_saips	-0.0550**	0.0500*	-0.105**	-0.0787	-0.174	-0.0396	-0.235*
	(0.0273)	(0.0290)	(0.0500)	(0.0579)	(0.121)	(0.0723)	(0.140)
lTOTAL_sav	0.00435	-0.00747**	-0.00237	0.00188	-0.000251	0.00250	0.000872
	(0.00316)	(0.00337)	(0.00580)	(0.00672)	(0.0141)	(0.00839)	(0.0162)
lTOTAL_incom	0.000374	-0.00109	-0.0143**	-0.0106	-0.0332**	-0.0148*	-0.0339**
	(0.00321)	(0.00341)	(0.00588)	(0.00681)	(0.0142)	(0.00850)	(0.0164)
avrg_plot_dist	0.000137	-0.000368	0.00446***	0.00743***	0.00991***	0.00638***	0.0177***
	(0.000691)	(0.000736)	(0.00127)	(0.00147)	(0.00307)	(0.00183)	(0.00354)
yrs_lvd_vlg	-0.000982	-0.00103	-0.00226*	-0.00272*	-0.00662**	-0.000324	-0.00419
	(0.000666)	(0.000709)	(0.00122)	(0.00141)	(0.00296)	(0.00177)	(0.00341)
got_ext	-0.0214	0.00290	0.0682	0.0958*	0.142	0.00986	0.138
	(0.0263)	(0.0280)	(0.0482)	(0.0558)	(0.117)	(0.0697)	(0.135)
info_inpt_mkts_price	0.118***	0.0330	0.0445	-0.0672	0.0218	-0.0862	-0.305*
	(0.0335)	(0.0357)	(0.0615)	(0.0712)	(0.149)	(0.0889)	(0.172)
Constant	0.197**	0.284***	0.207	0.102	0.470	0.360*	0.682*
	(0.0773)	(0.0823)	(0.142)	(0.164)	(0.344)	(0.205)	(0.396)
p- value	**0.0178**	**0.3828**	**0.0009**	**0.0000**	**0.0054**	**0.0142**	**0.0000**
R-squared= 26.13							

Note Standard errors in parentheses. *, **, and * are levels of significance at 10%, 5% and 1% respectively**

Additionally, **prtcpn_score** (Participation score) which was another component of the social capital, influenced uptake of combinations in cluster 4 and 7. Participation score was calculated from the participation level in groups by household members where they were members. The maximum participation level was 6, and the least was 1. The combination of cluster four was majorly dominated by a variety of seed and intercropping and additional minimum tillage while those in cluster 7 was only variety. When a household participation score improved by 1 value, adoption of combination in clusters 4 and 7 increase by 0.17 and 0.38 units respectively at 5% level of significance each. Participation in groups improves chances of interaction and learning. Inactive members are less likely to learn a lot from group members. Through the interactions of group members, they were more likely to know many people from who they can get help, acquire seeds from and other farming practices that are beneficial in the production of maize and legumes. They are also able to organize for cheap transportation of seeds from dealers and at a subsidized rate and cheap transport. The study agreed with that of Pratiwi and Suzuki (2017) who found that individuals who occupy a central position in their neighborhood and networks such as groups were better in learning outcomes. In their study, Sidique and Hadi (2016) found out that active participation in leadership roles in the community and institutions is important to adoption decisions to many people in the community especially where extension services are inefficient. They cited that the leaders and active participants do not only act as opinion leaders but also reference point from where other people learn from. Nato *et al.*(2016); Willy and Holm-Müller, (2013) on their studies also found active group involvement and social support to be forms of social capital that significantly influenced adoption of optimal and appropriate agricultural practices. Similarly, they too did not find social networks and collective action to be significant in adoption decisions of optimal agricultural practices. This is because it involved personal responsibility and boldness to take up the initiative to undertake the practices trained in practice.

The variable **recvd_info_saips** (Received information about sustainable agricultural intensification practices) represented those households that that received information about SAIPs. It was significant in the uptake of combinations in cluster 2. The combinations in this cluster were a variety of the seeds, fertilizer, and intercrop which were common but with some adding manure and rotation. In fact, a household that received information improved chances of adopting combinations in cluster 2 by 0.05 but reduced chances of adopting combinations in cluster 1, 3 and 7 by 0.06, 0.11 and 0.24 respectively, all at 5% level of significance. Information about SAIPs was important in the uptake of the optimal combination that will yield output (Baumgart-getz *et al.,* 2012). The possible scenario in this context was that the extension officers or groups from where households got training emphasized on the combinations cluster 2. This cluster composed of commercial inputs blended with manure, rotation, and intercrop. The study tends to support earlier findings by Challa *et al.* (2014); Cochrane and Lake (2014); Teklewold *et al.* (2014); Ogutu and Obare (2015) who found that source of information about any agricultural production technique is important in adoption decision. They all cited that information is an important aspect of the decision-making process of a household. The information also had to be from a reliable source to make an impact in the lives of the household.

Like receiving information about SAIPs, **info_input_mkts_price** (Received information about input market prices) was significant in the uptake of cluster seven which comprised of the variety of seed used in planting. For a household to know the prices of inputs in the market, awareness was important. This could be done through advertisements, individual trips of traders and agro-vets to the village and or extension officers. Other informants could be friends or relatives who may have bought these inputs or received this information and share with those who they think could be in need. Just like information about SAIPs was important, awareness about the prevailing market prices was also important. This could help in generally accessing the cost of production and alternatives available. Bearing this in mind, inputs are of varied nature and sizes, therefore important in knowing the quantity needed in the plot owned by the household. Another reason for households to have an idea of the selling price of inputs, which in this context included: seeds, fertilizer, and manure for those who did not have their own. was the fact that there exists price discrimination. A rational farmer whose motive is to minimize the cost of production must know where the prices were low for the same item. The finding of the study showed that those who got information about input prices improved adoption of combinations in cluster 1 by 0.12 at 10% level of significance and cluster 7 by 0.31 at 1 % level of significance. These combinations essentially composed of a variety of seed, manure, and fertilizer. The result agrees with Sidique and Hadi (2016) that training informs of extension services is central to the adoption of Sustainable Agricultural Practices in less developed economies. They continued to argue that SAIPs packages that are likely to yield more output should be encouraged to be adopted to improve yield and reduce hunger of any kind. Access to and quality information is key to adoption decisions (Baumgart-getz *et al.,* 2012)

A household made savings to use in the future date. They made savings in commercial banks, savings group, SACCOs, and microfinance. **lTOTAL_sav** (The total amount of money that a household saved) influenced uptake of combinations in cluster 2. The result indicated that increase in savings of a household by KES 1000 reduced chances of adopting combinations in cluster 2 by 0.22 at 10% level of significance. The study however expected that the more savings one makes could increase chances of one adopting more of commercial inputs in cluster 2. An explanation could be that some household made savings to fixed accounts or retirement benefits rather than saving to use later in buying inputs. It is also possible that some household has been planting maize and legumes over time and do not realize returns on their investments and therefore opt to save and use in other business ventures. Similarly, they could be practicing majorly production for consumption, while doing business to raise income.

The income of smallholder maize-legume households was received from farming, salary employment, businesses, offering labor, through remittances in kind and from renting out plots to others. Just like savings, lTOTAL_income (The natural logarithm of the total amount of income that a household received) was significant in the uptake of combinations of cluster 3, 5 and 7. An extra KES 1000 inform of income to the household reduced chances of practicing combinations in clusters 3 by 0.14 units, cluster 5 by 0.03 units and cluster 7 by 0.03 all at 5% level of significance and cluster 6 by 0.01 units at 1% level of significance. Cluster 3 and 5 are more of variety and conservation agricultural practices whereas cluster 7 is variety alone. This implies that when income increases, a household is more likely to combine variety and probably more other commercial inputs and or other conservation practices. When income rises one is able to purchase more of commercial inputs and combine them in the production of maize and legumes (Sidique and Hadi, 2016). This is more especially when the extra income comes from sales of the production of the previous season. Higher incomes in the household were also found to be significant in the adoption of maize-legume rotation and residue retention by (Manda, Alene, Gardebroek, Kassie, and Tembo, 2016) in Zambia. It is easy to purchase and transport farm inputs when one has the money or has a higher income. Those who also supplement their income from credit borrowing are also more likely to improve on commercial inputs because of improved financial capacity (Baumgart-getz *et al.,* 2012).

Households in the maize-legume system had plots in different locations from the homestead. Some were near their homesteads while some were far away that involved walking for over one hour to their location. It was worth noting that some did not own land and therefore rented in for farming and this could depend on where they found it. The findings of the study indicated that **avrg_plot_dist** (distance of the plot from household homestead) was significant because, a household that had their plots far were more likely to adopt combinations in clusters 3, 4, 5, 6 and 7. An extra 100 minutes' walk distance from the homestead increased adoption of combination in cluster 3 by 0.44 times; cluster 4 by 0.74; cluster 5 by 0.99 times; cluster 6 by 0.64 and finally cluster 7 by 1.77 times. All of them were significant at 10% level of significance. Most of the combinations in this clusters included variety and conservation practices. The justifications behind this could be that they do not want to invest so much in plots that are far since they incur a cost in transportation may be and because the far the plot is, the less one is likely to manage it effectively. That is why they may opt for minimum tillage, manure which is less expensive compared to fertilizer and intercropping to maximize productivity per unit area. According to Teklewold *et al.* (2014), plot distance from the homestead was significant, alluding that the far the plot was from the homestead, the less likely one could choose practices that are labor intensive like manure. Manure is bulk and needs a means of transport to far plots.

The time one household had lived in the village varied from one household to the other. The **Agehh** (the age of the household head/ decision maker) and **yrs_lvd_vlg** (the years a given household has lived in the village) also influence uptake of given specific clustered. These variables could be pegged to the experience one has gained over time and in the village and probably the number of people they have known over time from whom they can get help. The empirical results of the study showed that household that had lived more years in the village were less likely to adopt combinations of SAIPs in cluster 3, 4 and 5. When a household lived in the village for 10 years, it reduced chances of adopting combination in cluster 3 by 0.02 times at 1 % level of significance, cluster 4 by 0.03 times and cluster 5 by 0.06 times both at 5% level of significance. The reason behind the low uptake of those clusters could be because experience has shown that the combinations of them yield less.

On the other hand**,** households that were 10 years older practiced less of combinations in cluster 6 by 0.05 times compared to those which were younger, at 5% level of significance. This cluster had combinations that were more soil conservation. They include crop rotation, intercropping and manure in addition to variety. It could be that over time, they have practiced these combinations and realized low output, hence shying away from them. It is also possible that some of these households have saved over time and therefore can afford more of commercial inputs. The study confirmed earlier findings by Challa *et al.* (2014); Cochrane and Lake (2014); Teklewold *et al.* (2014); Ogutu and Obare, (2015) that age of the household head is important in adoption decision making. However, Arslan *et al.*, (2014) did not find the age of the household head to be significant, citing that only extension services and rainfall variability only affect adoption of conservation agricultural practices.

7. Conclusion and Implications

Adoption of a combination of SAIPs is considered as a remedy to the many production challenges that many smallholder maize-legume farmers are facing in Kenya. The study analyzed different combinations that were clustered into seven components composed of homogeneous combinations that were formed using Principal component analysis. The index of different SAIPs combination for the household was used as the dependent variables against social capital among other explanatory variables. The descriptive statistics showed that 32% of the respondents in Bungoma; 30% in Tharaka Nithi; 29% in Embu; 31% in Meru and 31% I Siaya received information about SAIPs. This is an average of 31% across the panel. A further lower percentage of those who received information about input prices was reported at 16.2%. This implies that many of the households in the maize-legume system in Kenya do not receive information which is important in adoption decision. Summary statistics showed that average age of the household head was 52 years. On average the natural logarithm of the total amount of money a household saved and the amount they got as income was 7.4 and 9.3 respectively across the panel. The trend for saving and income was relatively higher in the beginning, with a slight drop in the midline and a rise in the end line. Average distance from household homestead was ten minutes' walk. The regression results showed that social capital was not significant in explaining combination adoption of the SAIPs, except for the cognitive aspect of social capital and participation score in group institutions where they were members. Other factors that were significant included the age of the household head, if the household received information about SAIPs and input prices, amount of money that a household saved and that which they received as income. The number of years one had lived in the village was also significant in explaining adoption decisions of a combination of SAIPs. Going forward, the policy must consider encouraging and promoting better access to information to smallholder maize-legume farmers, encourage membership and participation to benefit groups and finally enhance government institutions that offer advice and training since most households may have more trust in them than other different sources.

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10. Appendixiture

Appendix 1: How combinations were chosen

Combinations	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Commonality
V	0.0933	-0.0018	0.0523	-0.0853	0.2633	-0.3786	**-0.4729**	0.455019
Vf	-0.0851	0.0537	0.0462	-0.0475	**0.5054**	-0.1780	0.0631	0.305611
Vfi	-0.0600	**0.4963**	-0.0732	0.0958	-0.0067	-0.1378	0.1118	0.295983
Vi	-0.0884	0.0481	-0.0767	**0.6367**	-0.0953	0.0003	-0.0614	0.434250
Vm	0.0138	-0.0335	**0.6939**	-0.0696	-0.0511	0.0079	0.0013	0.490329
Vmf	0.0719	0.0131	0.0374	-0.0622	0.0447	-0.0489	0.7541	0.583665
Vmfi	0.0020	**0.5492**	0.0444	-0.0558	-0.1400	-0.0615	0.0273	0.330837
Vmi	-0.0406	0.0833	0.0807	-0.0769	**-0.5841**	-0.0644	0.0462	0.368468
Vr	0.0346	0.2588	0.0658	-0.0827	0.3202	**0.3824**	-0.1964	0.366674
Vri	-0.0476	-0.0330	-0.0159	0.0144	0.0121	**0.7007**	0.0198	0.495334
Vrm	**0.5036**	-0.0458	0.0458	0.0054	0.0653	0.1311	-0.0003	0.279289
Vrmf	**0.5566**	0.0211	0.0015	-0.0434	0.0416	-0.0629	0.0868	0.325356
Vt	-0.0221	-0.0356	-0.0148	0.0325	**0.3686**	0.1458	0.2719	0.234084
Vit	0.0857	-0.0306	0.0833	**0.7244**	0.0833	0.0083	0.0001	0.546983
Vmt	-0.0354	0.0302	**0.6879**	0.1093	0.0278	-0.0194	0.0270	0.489196
Vrfi	0.0470	**0.6033**	-0.0046	-0.0003	0.0656	0.1005	-0.0496	0.383065
Vrmfi	**0.5939**	0.0297	-0.0637	0.0818	-0.0805	-0.0984	0.0218	0.380986
Vrmi	0.1861	-0.0093	0.0366	-0.0681	-0.1943	0.3094	-0.2460	0.234694