

**Essays on Financial Inclusion, Food Security and Nutrition in Developing
Countries**

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Abstract

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Essays on Financial Inclusion, Food Security and Nutrition in Developing Countries

by Hamidou JAWARA

This dissertation is focused on two main issues that continue to attract huge attention in the development economics discourse: Food security and nutrition and financial inclusion. These two issues are studied in three chapters. Thus, food security and nutrition is covered in chapter one and financial inclusion is covered in chapter two and three.

In looking at food security and nutrition, the study here is concentrated on the elasticity of nutrient intake to changes in wealth. The study of the relationship between nutrient intake and wealth for poor households continue to be an issue of huge policy relevance. Therefore, we contribute to the ongoing debates on the nutrient income elasticity using a sample of ultra-poor (i.e. with orphans and vulnerable children-OVC) households in Kenya. To estimate nutrient income elasticity for these households, we used data for the evaluation of the Kenya Cash Transfer OVC project and panel data techniques that address measurement error and simultaneity bias. In addition, we also used semi-parametric panel data models to address nonlinearities. For majority of the nutrients considered in our study, we find that they have an income elasticity that is inelastic and significantly different from zero. Furthermore, we also find that caloric intakes are more inelastic to changes in wealth than macro and micro nutrient intakes. Overall, the results support the evidence that dietary behavior does response to changes in wellbeing. Therefore, development policies that target wellbeing can also promote better nutritional outcomes and food security in ultra-poor households.

Despite the gains being mixed, financial inclusion is still heralded as an essential tool in the fight against global poverty; in particular, for the achievement of the 2030

agenda. This is rationalized by the fact that still lot of people, particularly in developing countries, lack access to basic financial services. Lack of access to financial services entrenches poverty because it makes consumption smoothing more difficult. It is for this reason, supported by empirical evidence, that it is a widely held belief that access to finance can stimulate a positive change in welfare. Hence, in this dissertation I used individual and household survey data from Gambia to study two aspects of financial inclusion: First, I study the impact of access to formal financial services like basic saving on household outcomes such as total spending, ownership of durable assets, health spending, and education spending. Using a representative household survey and kernel ridge regression method, I find that household access to formal means of savings has a positive and statistically significant impact on all the outcomes of interest except health spending. Furthermore, I find the largest effect size of 73% for education expenditure. However, the impact estimates on education and food expenditure are not very robust to mild presence of hidden bias. Hence, overall I find robust impact for total expenditure and asset ownership. Second, I study whether personality traits can affect repayment behavior of a borrower in a joint liability lending scheme. To this effect, I use a big five inventory consisting of 30 items to measure non-cognitive traits. The 30 items are then grouped into five main sub-groups commonly known as the Big Five Inventory in Psychology. A borrower rate herself on each of the items and the standardized score of a borrower in each element of the subgroups is determined and this is related to the probability of the borrower to default on her part of a group loan. Using data from an NGO-based microcredit program in Gambia, I find that personality traits such as Extraversion, Agreeableness, Neuroticism, and Openness to Experience matters for the likelihood of default. In particular, an increase in the amount of these traits is associated with lower probability of default. Hence, the evidence I find is an indication that asymmetric information problems (in particular adverse selection problems) are real in microcredit markets; at least true for the context studied. Therefore, the inclusion of personality trait instruments among the screening devices used by micro-lenders could enhance the performance of these schemes. This is quite useful for developing countries as screening of borrowers is difficult due to lack of data on financial history.

Note that the the first chapter is a joint work with Rainer Thiele and the other two chapters are individual works.

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List of Abbreviations

AFI	Alliance (for) Financial Inclusion
ATE	Average Treatment Effect
ATT	Average Treatment (effect on) Treated
BFI	Big Five Inventory
CBEMP	Capacity Building Economics Management Project
CD	Cragg Donald
CBG	Central Bank (of The) Gambia
CT	Cash Transfer
DR	Doubly Robust
DFA	Discriminat Function Analysis
EA	Enumeration Areas
FI	Financial Inclusion
FFM	FiveFactor Model
GAWFA	Gambia Women Finance Association
GBoS	Gambia Bureau of Statistics
GDP	Gross National Product
GMD	Gambian Dalasi
GMM	Generalized Method (of) Moment
GSS	Generalized Social (of) Survey
IHS	Integrated Household Survey
IV	Instrumental Variable
LG	Large Group
KRRM	Kernel Ridge Regression Matching
ME	Measurement Error
NEO	Neurotism Extraversion Openness
NGO	Non Governmental Organization
NNM	Nearest Neighbor Matching
OLS	Ordinary Least Square
OPM	Oxford Policy Management
OVC	OrphanVulnerable Children
PHDCN	Project (on) Human Development (in) Chicago Neighborhood
PSM	Propensity Score Matching
RCT	Randomized Control Trial
SDG	Sustainable Development Goal
SG	Small Group

SSA	Sub Saharan Africa
SST	Sen Shorrock Thon
UNDP	United Nation Development Fund
UNESCO	United Nation Educational Scientific Cultural Organization
UNICEF	United Nations Children's Fund
VISACAS	Village Savings And Credit Associations
ROSCAS	Rotating Savings And Credit Associations
WB	World Bank

*Dedicated to my wife Fatoumata Singhateh and daughter
Salimatou Jawara*

Chapter 1

Nutrient Income Elasticity in Ultra-Poor Households: Evidence from Kenya

1.1 Introduction

Motivated by the assertion that hunger and poverty tend to be synonymous ([Banerjee and Duflo, 2011](#)), i.e. the prevalence of hunger and malnutrition is associated with poor economic status, a significant amount of mostly empirical literature on the relationship between nutritional status and income or total expenditure has emerged over the last decades ([Ogundari and Abdulai, 2013](#)).

Theoretically, two explanations can be given on why nutrition might be related to income or expenditure. The first is the efficiency-wage hypothesis ([Leibenstein, 1957](#); [Mirrlees, 1957](#); [Stiglitz, 1976](#)), according to which employers reward labour based on productivity and the latter is determined by nutritional status. Thus, unemployment and therefore poverty exists because some people do not have enough to eat ([Subramanian and Deaton, 1996](#)). The second explanation, which has dominated much of the academic literature, is that nutrition status is determined by income and food demand ([Subramanian and Deaton, 1996](#)). Accordingly, nutritional problems such as malnutrition, which is assumed to be associated with underdevelopment, would be attenuated by economic prosperity ([Abdulai and Aubert, 2004](#)). This latter argument has motivated a long-standing debate on whether what [Subramanian and Deaton \(1996\)](#) called a "calorie Engel curve" exist or not for the poor. A calorie Engel curve would imply that the poor switch from poor quality food but less expensive calories to more expensive calories but high-quality food as income

increases (Skoufias et al., 2011). Therefore, the primary behavioural parameter of interest in these debates is the calorie-income elasticity (Gibson and Rozelle, 2002).

Some empirical studies have estimated the calorie-income elasticity, but the evidence is still mixed (Santeramo and Shabnam, 2015). In particular, while some authors (such as Behrman and Deolalikar, 1987; Bouis and Haddad, 1992; Skoufias et al., 2009) find that the responsiveness of calories to income changes is not significantly different from zero, others (e.g. Subramanian and Deaton, 1996; Abdulai and Aubert, 2004; Aromolaran, 2004; Skoufias et al., 2011) obtain a positive and statistically significant calorie-income elasticity. This has important policy implications: If it is true that nutrient intake does not respond to changes in income, then, common interventions such as cash transfer programs will not suffice to eliminate malnutrition and food insecurity.

Against this background, the objective of this study is to provide new evidence on the nutrient-income elasticity in a setting of impoverished households in Sub-Saharan Africa. Most of the evidence so far is from Asian and Latin American countries and does not cover the very poorest households. By contrast, we consider ultra-poor households, i.e. households with orphans and vulnerable children (OVCs), in Kenya. The size of this group is non-negligible: It is estimated that there about 2.6 million OVCs in Kenya and 12% of all households have at least one OVC (Lee et al., 2014). Lee et al. (2014) estimate that more than half of OVC households are in the lowest two quintiles of the wealth distribution in Kenya and 22% of them have experienced moderate to severe food shortages. Studying whether income gains may help impoverished households in Kenya improve their nutritional status is thus highly policy-relevant, especially at a time when social programs to tackle food and nutrition problems are ubiquitous in the country.

Another notable feature of our study is that besides calorie elasticities it also provides evidence on the elasticity of other (macro and micro) nutrient intakes to changes in income. Most of the debates on the relationship between dietary behaviour and changes in income have focused on caloric intake, but calories are not the only important component of human diets. As highlighted by Skoufias et al.

(2009), a positive relationship between energy intake and income does not necessarily translate into a significant positive relationship between nutrient intake and income and vice versa. Households may, for example, use additional income to switch to more nutrient-rich foods with the same calorie content. It is therefore essential to also investigate the impact of income on the intake of macro and micronutrients. The macronutrients we study are protein, fat, and fibre and the micronutrients are vitamins (A, D, and Folate) and minerals (zinc, iron, and calcium). There is evidence that higher intake of these nutrients is associated with better health via a reduction in malnutrition and other nutrient-deficiency-related health problems such as anaemia.

Furthermore, we contribute to the methodological debate on the issue of non-linearities that arise if nutrition elasticities differ between income groups. In particular, the calorie-income elasticity may be higher for poorer household, who have insufficient food to eat, than for richer households. This issue was first raised by [Strauss and Thomas \(1990\)](#) who found for the case of Brazil that indeed the calorie-expenditure elasticity is higher for poorer households. They concluded that this non-linearity could not be adequately captured in a fully linear parametric model. Following their land mark study, the use of complete nonparametric techniques to estimate calorie-income elasticity grew in popularity (e.g. [Subramanian and Deaton, 1996](#); [Skoufias, 2002](#); [Abdulai and Aubert, 2004](#); [Skoufias et al., 2011](#)). Complete nonparametric models are desirable because they allow for curvature without imposing any functional form on the data ([DiNardo and Tobias, 2001](#)). However, they pose a major drawback in that they prevent the inclusion of a large set of control variables; particularly, variables that are known to follow a particular parametric form. Hence, partial-linear models that allow for the inclusion of variables in both parametric and nonparametric fashion can be considered as good comprises between fully parametric and nonparametric models ([Rodriguez-Poo and Soberon, 2017](#)). In our case, this is desirable because it allows for a flexible characterisation of the nature of the relationship between wealth and nutrients intake while at the same time allowing for other covariates to be controlled for in a parametric fashion. For this reason, we employ the partial-linear panel data model suggested by [Baltagi and Li \(2002\)](#) to control for possible nonlinearities in the relationship between nutrient intakes and

wealth. To the best of our knowledge, [Tian and Yu \(2015\)](#) study on China is the only previous study that used this approach.

In addition to dealing with non-linearity, we also address the problems of measurement error and simultaneity bias. Meta-Analyses by [Ogundari and Abdulai \(2013\)](#), [Santeramo and Shabnam \(2015\)](#), and recently by [Colen et al. \(2018\)](#) have pointed to differences in dealing with these methodological flaws as critical factors behind the heterogeneity in estimated nutrient-income elasticities. We use the approach developed by [Lewbel \(2012\)](#), recently extended to panel data by [Meijer et al. \(2017\)](#) to address the measurement error problem, and standard panel IV estimation to tackle the problem of simultaneity bias and measurement error. Given that the [Meijer et al. \(2017\)](#) approach is valid under the assumption that model suffers just from measurement error bias, the instrument generated via this procedure might not be consistent. We check for this by estimating the main model of interest with both the standard instrument and generated instruments used as instruments. Results indicate that the instrument generated via [Meijer et al. \(2017\)](#) generally tend to over-correct for the OLS bias.

The remainder of the chapter is organized as follows: In section 1.2, we discuss the data used in the empirical analysis and provide some descriptive statistics. Section 1.3 introduces the estimation methodology, while Section 1.4 discusses the results. Section 1.5 summarizes the main findings and concludes.

1.2 Data and Descriptive Statistics

The data we use were collected for the evaluation of the Kenya cash transfer program for orphans and vulnerable children (Kenya CT-OVC in short). The Kenya CT-OVC is a safety net program run by the government with the primary objective of offering social protection to ultra-poor households, i.e. households with orphans and vulnerable children. It takes the form of a regular monthly income transfer of initially Ksh 1500 (about 20) per household, which has been increased over time to capture price changes. An OVC household is defined as a household that satisfies one of three criteria: there exists at least one single or double orphan; the primary caregiver is chronically ill, or the head is chronically ill ([Handa et al., 2016](#)). OVC

status plus other variables such as age of the main caregiver, education level, asset ownership, access to clean water and sanitation were the leading indicators used in the program targeting (See [Handa et al., 2012](#), for details).

The government of Kenya and UNICEF piloted the program in 2004 and since then has reached over 350,000 beneficiaries. Following its success in the piloting phase, it was adopted into the national budget in 2007 as a government flagship social protection program, and consequently, there was an agreement for it to be expanded to other regions of the country. Before this expansion was effected, an evaluation of the program was commissioned by UNICEF and contracted to a private consulting firm, the (OPM) Oxford Policy Management ([The Kenya CT-OVC Evaluation Team, 2012](#)). The evaluation was carried out in seven districts. Three rounds of surveys were carried out between 2007 and 2011: a baseline survey in 2007 and two follow-up surveys in 2009 and 2011. The number of eligible households surveyed in the baseline was 2,294, and there was, respectively, a 17% and 5% attrition between baseline and first follow-up in 2009 and between first follow-up and second follow-up in 2011 ([Handa et al., 2016](#)).

Since one of the objectives of the program was to improve food security in OVC households, information on household food consumption was collected alongside other household indicators on health, education, and children welfare. In this study, we use data on household characteristics, village-level characteristics, and food consumption to study the calorie or nutrient income elasticity for households. Specifically, we use age of the household head, gender of the household head, education level of the household (measured as the number of adults in a household with at most 8 years of education), household size, household total expenditure (measured as the sum of food and nonfood expenditure), and different household demographic ratios (such as proportion of children under 5, under 14, under 16, proportion of adults, and proportion of old people) as indicators of household characteristics. Distance to the nearest market and access to a road network serve as village level characteristics.

In collecting the food consumption data, households were requested to make a recall of 29 food items that they consumed in the last seven days before the day of their interview. For each food item, information on total outlays, the main source, as

well as the quantity and unit consumed, were collected. Also, local market prices of 19 food items were collected using a questionnaire that was administered at the community level. We use this information to construct food availability in a household from which per-capita caloric and nutrient intake from 13 food items (maize flour, Irish potato, beans, bananas, kale, beef with bones, dried fish, eggs, milk, cooking oil, sugar, salt, and tea leaves) consumed by the household is computed. In doing so, we first divide household monthly total expenditure on each food item by the minimum locality price per unit (kilogram or litres) of that food item, where minimum prices are computed from the report of local prices at the community level. This allows us to obtain quantities of the different food items consumed by each household.¹ We considered food from all sources (purchased, own production, and received as gifts); food from own production and received as gifts were valued at the prevailing local market price. Since the information available is not enough to compute actual consumption of food by each household as wastage and leftovers or food to guest and worker are not accounted for, we only capture food availability, which could result in an overestimation of our calorie- or nutrient-wealth elasticities. Second, we convert the unit of measurement of each food item from kilogram and litres to grams and millilitres. Third, to derive total calorie or nutrient intakes from a food item, we multiply the total number of grams or millilitres of household consumption of that food item by the number of kilocalories or nutrient available in a 100 grams edible portion. We use the food composition table of Tanzania by [Lukmanji et al. \(2008\)](#) for the conversions in this step. The total caloric or nutrient intake from a food item can then be summarised as

$$C = \sum_i q_i c_i \quad (1.1)$$

where q_i is the total number of grams or milliliters of food i ($i = 1, 2, 3, \dots, 13$) consumed by a household and c_i is the calorie or nutrient equivalent unit of food item i . Finally, we compute per-capita calorie or nutrient intake by dividing total caloric or nutrient intake (given as C_j) of each household by the adult equivalent

¹ Even though some of the questionnaires collected information on the exact quantities that were consumed and the units involved, this information was not collected in all survey rounds. Thus, for the sake of consistency, we rely on the above procedure to derive quantities consumed.

unit of that household using the adult equivalent scales from [Anzagi and Bernard \(1977\)](#). For the analysis below, we categorise the food items into food groups. The total number of calories from a food group is given as the sum of per-capita calories or nutrients from all the items in that food group, i.e. for food group g with j food items we obtain

$$C_g = \sum_j C_j \quad (1.2)$$

In our case, we define nine food groups: cereal, tuber, pulse, fruit, vegetable, meat, milk, oil, and sugar. To minimise the effect of outliers, we winsorize the values of all the measures computed here at their *2nd* and *98th* percentile; that is all values below and above the *2nd* and *98th* percentile, respectively, are set to these percentiles. Given that the design of the evaluation was longitudinal, the data collected for the three periods can be used to construct a panel dataset on households' food consumption. To ensure we are dealing with a balanced panel, we focus on households that were surveyed in all three rounds; households surveyed in the baseline but not surveyed in the follow-ups are dropped from the analysis. Pooled over the three rounds, this gives a total of 5346 observations. Note that the evaluation of the program targeted only poor rural households. Our sample is therefore not representative of all households in Kenya but represents only those with characteristics similar to the targeted group.

Table 1.1 reports summary statistics for the household and village-level characteristics. Each statistic is shown for OVC households in the bottom and top quartile of the wealth distribution (given in terms of per-capita household total expenditure), as well as for all the OVC households in the sample and each period. It can be seen that the average age of OVC household heads is about 61 years in the baseline (2007) and a bit lower in the subsequent years. As expected, poorer OVC households are much bigger than richer OVC households. However, in terms of the composition of the different age groups in the households, the two samples do not differ significantly. Household per-capita expenditures increase over time for all households. In the overall sample, there was a rise of about 75% and 25%, respectively, in 2009 and 2011, which may at least partly be due to the positive income shock created

TABLE 1.1: Household and Village Indicators

Year	Bottom 25 %			Top 25 %			Pooled		
	2007	2009	2011	2007	2009	2011	2007	2009	2011
Age (Head)	61.42	56.99	59.43	57.28	58.50	60.06	61.33	57.58	58.00
Female (Head)	0.62	0.59	0.56	0.67	0.70	0.65	0.64	0.65	0.63
Education (Head)	1.22	1.45	1.74	0.65	0.70	1.09	1.11	1.12	1.28
household size	6.17	7.43	7.76	3.99	4.34	4.66	5.62	5.70	5.73
Expenditure (Ksh, 000)	2.73	3.17	3.17	11.45	13.18	14.67	4.50	7.89	9.92
ChildU6 (proportion)	0.13	0.13	0.089	0.13	0.10	0.071	0.13	0.11	0.08
ChildU14 (proportion)	0.28	0.22	0.27	0.32	0.29	0.27	0.28	0.26	0.27
ChildU18 (proportion)	0.20	0.03	0.20	0.11	0.04	0.18	0.19	0.04	0.19
Adult (proportion)	0.14	0.31	0.28	0.20	0.19	0.23	0.21	0.24	0.25
Old (proportion)	0.14	0.11	0.12	0.18	0.20	0.20	0.16	0.15	0.17
Market (minutes)	41.95	34.41	38.30	39.75	30.75	42.57	43.41	32.12	39.35
Road (proportion)	0.72	0.95	0.76	0.80	0.91	0.76	0.72	0.92	0.76
Price of calorie (Ksh, 00)	1.86	2.23	4.24	2.09	2.86	4.78	1.90	2.59	4.55

Descriptive statistics of household and village level covariates. Bottom 25 % = Households with per capita expenditure in the bottom quartile of the wealth distribution; Top 25 % = Households with per capita expenditure in the top quartile of the wealth distribution; Pooled = All households in the sample. Reported are the means of each covariate in each sub-sample as well as in the overall sample by year. Note that all the continuous variables were winsorized at 2%; this was done in order to dampened the effect of outliers on the estimation of the means.

by the cash transfer. Increases are more pronounced for richer than poorer OVC households; between 2009 and 2011, the poor OVC households did not experience any rise in per-capita expenditure. Education levels also improve over time for both poor and rich OVC households as well as in the overall sample. Interestingly, poorer OVC households tend to perform better on education than richer OVC households; this happens even at baseline so could not be due to the cash transfer. Price of calorie, given as the ratio of total expenditure to total calories of all food items, is used to measure food quality in the two groups. In general, food quality improves over time for all households, but OVC households in the top quartile invest more in quality food than those in the bottom quartile. The village-level characteristics (distance to a market and access to a road) do not differ significantly across the two groups of households.

Summary statistics on nutrient intakes are given in Table 1.2. Average per-capita energy intake by OVC households in the bottom quartile is generally much lower

TABLE 1.2: Macro and Micro Nutrients

Year	Bottom 25 %			Top 25 %			Pooled		
	2007	2009	2011	2007	2009	2011	2007	2009	2011
Calorie (<i>kcal</i> ,000)	3.40	3.48	2.28	9.02	9.18	6.66	4.69	6.44	5.15
Protein (<i>kcal</i> ,000)	0.29	0.31	0.22	0.86	1.01	0.67	0.43	0.65	0.51
Fat (<i>kcal</i> ,000)	0.65	0.53	0.58	2.09	1.68	1.71	0.95	1.10	1.29
Fiber (<i>kcal</i> ,000)	0.21	0.25	0.14	0.48	0.59	0.41	0.28	0.43	0.32
Vitamin A (μg)	44.26	170.17	51.45	162.42	489.38	485.23	69.47	332.83	292.26
Vitamin D (μg)	0.28	0.15	0.47	1.25	0.72	1.66	0.51	0.42	1.21
Folate (μg)	312.27	369.30	252.98	1064.67	1142.63	852.09	488.42	763.27	619.60
Iron (<i>mg</i>)	26.59	31.55	17.40	62.14	76.30	54.88	35.58	55.33	41.71
Zinc (<i>mg</i>)	14.15	15.22	9.44	38.68	41.98	29.40	20.05	28.84	22.54
Calcium (<i>mg</i>)	425.09	307.20	363.33	1663.93	1265.36	1172.35	725.44	785.17	862.52
Arginine (<i>mg</i>)	3302.93	3438.63	2326.49	9019.92	9660.42	7780.38	4734.04	6599.27	5834.39
Histidine (<i>mg</i>)	2298.89	2442.64	1669.84	7021.75	7356.37	5782.98	3445.81	4914.50	4291.56
Lysine (<i>mg</i>)	2993.18	2936.84	2618.08	10697.22	10731.18	9043.61	4880.28	6749.10	6592.04
N	916	251	147	88	471	755	1782	1782	1782

Average macro and micro nutrients intakes of the OVC households. Bottom 25 % = Households with per capita expenditure in the bottom quartile of the wealth distribution; Top 25 % = Households with per capita expenditure in the top quartile of the wealth distribution; Pooled = All households in the sample. Reported are the average nutrient intake in each sub-sample as well as in the overall sample by year of survey. Note that the variables were all winsorized at 2%. Note: N= number of observations; *kcal*= Kilo calories; *mg* = milligrams; μg = micrograms.

than energy intakes by OVC households in the top quartile of the per-capita consumption distribution. A similar pattern is observed for both the intake of macro (protein, fat, and fibre) and micro (vitamins, minerals, and amino acids) nutrients. For example, in the case of a mineral like iron, a deficiency of which is a cause for anaemia that remains a hurdle for many developing countries, there was a difference in favour of the top quartile of about 133% in 2007, 141% in 2009 and 215% in 2011. This evidence points to non-linearities in per-capita nutrients intake among OVC households, which we explore below using a partial linear panel data model.

Table 1.3 reports descriptive statistics on the share of calories attributable to the food groups, which is an indicator of food energy sources for the households. Both poor and rich OVC households get a significant share of their calories from cheap sources like maize flour, indicating their ultra-poor status, but the proportion of calories from cereal is higher for the former group. Healthy components of diets, such as

TABLE 1.3: Share of Calories

Year	Bottom 25 %			Top 25 %			Pooled		
	2007	2009	2011	2007	2009	2011	2007	2009	2011
Cereal	0.615	0.705	0.549	0.483	0.568	0.501	0.585	0.634	0.537
Tuber	0.007	0.002	0.006	0.034	0.009	0.009	0.011	0.006	0.008
Pulse	0.036	0.046	0.068	0.065	0.076	0.066	0.0458	0.061	0.063
Fruit	0.006	0.005	0.004	0.024	0.007	0.012	0.010	0.007	0.010
Vegetable	0.006	0.008	0.014	0.003	0.007	0.013	0.006	0.008	0.012
Meat	0.024	0.014	0.040	0.078	0.059	0.069	0.037	0.035	0.057
Milk	0.018	0.008	0.023	0.029	0.026	0.041	0.021	0.020	0.034
Oil	0.137	0.079	0.099	0.140	0.078	0.090	0.133	0.080	0.095
Sugar	0.148	0.105	0.074	0.144	0.143	0.084	0.150	0.127	0.084
<i>N</i>	916	251	147	88	471	755	1782	1782	1782

Average share of calorie of food groups Bottom 25 % = Households with per capita expenditure in the bottom quartile of the wealth distribution; Top 25 % = Households with per capita expenditure in the top quartile of the wealth distribution; Pooled = All households in the sample. Reported are the mean share of calories from the different food groups in each sub-sample as well as in the overall sample by year of survey. Note: *N*=number of observations.

fruits and vegetables, do not seem to be essential sources of calories for these households; still, they are a more important source of calories for top quartile than bottom quartile OVC households. Oil and sugar, which are associated with dietary diseases like Diabetes and heart-related diseases, are more important sources of calories (for both poor and rich OVC households) than fruits and vegetables.

Given the results from above, it is perhaps not surprising that a significant chunk of the OVC household's food budget - e.g. about 34% in 2011 in the overall sample - is on average spent on cereals (see Table 1.4). After cereals, oil and vegetables are the food groups that account for the highest portions of food budgets. However, both decreased over time, in particular for poorer OVC households.

The overall picture emerging from the descriptive statistics is that nutrient intakes, calorie shares, and food budget shares partly vary over time and across households with different wealth status. We will explore these observations in more detail in the econometric analysis below.

TABLE 1.4: Share of Food Expenditure

Year	Bottom 25 %			Top 25 %			Pooled		
	2007	2009	2011	2007	2009	2011	2007	2009	2011
Cereal	0.309	0.494	0.365	0.223	0.352	0.311	0.279	0.406	0.341
Tuber	0.050	0.030	0.034	0.049	0.043	0.038	0.048	0.035	0.040
Pulse	0.032	0.053	0.065	0.056	0.078	0.059	0.040	0.068	0.058
Fruit	0.016	0.023	0.018	0.030	0.023	0.027	0.020	0.024	0.024
Vegetable	0.137	0.117	0.085	0.073	0.083	0.069	0.122	0.097	0.073
Meat	0.077	0.073	0.071	0.247	0.202	0.196	0.124	0.147	0.152
Milk	0.089	0.078	0.085	0.056	0.077	0.061	0.079	0.084	0.066
Oil	0.0773	0.0714	0.0764	0.0555	0.0562	0.0583	0.0700	0.0620	0.0629
Sugar	0.0855	0.0822	0.0693	0.0682	0.0724	0.0626	0.0834	0.0783	0.0674
N	916	251	147	88	471	755	1751	1776	1754

Average food expenditure share of each food group. Note: Bottom 25 % = Households with per capita expenditure in the bottom quartile of the wealth distribution; Top 25 % = Households with per capita expenditure in the top quartile of the wealth distribution; Pooled = All households in the sample; N= number of observations. Reported are the average food expenditure share of each food group in each sub-sample by year.

1.3 Methodology

As highlighted above, three issues need to be addressed when estimating the calorie or nutrient-wealth elasticity: Measurement error, simultaneity bias, and non-linearity in the relationship between the two variables. We employ heteroskedasticity-restriction IV estimation proposed by [Lewbel \(2012\)](#) and recently extended to a panel data framework by [Meijer et al. \(2017\)](#) to address the endogeneity of total expenditure due to measurement error; standard panel IV methods to deal with both measurement error and simultaneity bias; and the partial linear panel data approach of [Baltagi and Li \(2002\)](#) to account for non-linearity in the relationship between nutrient or caloric intake and wellbeing.

1.3.1 Measurement Error and Endogeneity

We use total per-capita household expenditure on food and non-food items as a measure of wealth in an OVC household. Total expenditure is a better proxy of wealth than total income as it comes closer to measuring permanent income. Its

main drawback is that it may suffer from measurement error, e.g. because total expenditure does contain items that are not regularly purchased (Meghir and Robin, 1992). When total expenditure is combined with caloric availability in a regression model, this may be a source of common measurement error, which arises if total expenditure and caloric intake are derived from the same data source and as a result measurement error in one could correlate with measurement error in the other. This phenomenon is likely to occur in survey data where tendencies for error affect series of self-reported variables (De Nadai and Lewbel, 2016). Bouis and Haddad (1992) were the first to indicate that the common measurement error leads to a positive bias in estimated calorie-income elasticities. Thus, it is different from the classical error-in-variables problem that biases estimated coefficients towards zero, commonly known as the attenuation bias. Griliches and Hausman (1986) have shown that in the presence of measurement error the use of panel data techniques such as the within or between estimator will likely exacerbate such bias.

Conceptual Framework

The model we estimate can be described as:

$$Y_{nt} = X_{nt}\beta + r'_{nt}\delta + \alpha_n + \epsilon_{nt} \quad (1.3)$$

where Y_{nt} denotes the logarithm of per capita calorie or nutrient intake by household n at time t ; X_{nt} is the logarithm of per capita expenditure by household n at time t ; r_{nt} is a vector of exogenous covariates (including both household characteristics such as household size, age, and demographic ratios, and village-level indicators such as access to roads, markets, water and sewage systems) for household n ; at time t , which are assumed to be measurement error free; α_n denotes household fixed effects; and ϵ_{nt} is the error term with zero mean. Suppose X_{nt} cannot be observed as it is measured with error due to reasons outlined by Bouis and Haddad (1992), hence, because of the commonality of measurement error Y_{nt} is also mismeasured. Therefore, what we observe is Y_{nt}^* and X_{nt}^* with error φ_{nt} and v_{nt} , respectively. The

relationship between Y_{nt} and Y_{nt}^* and X_{nt} and X_{nt}^* is described as:

$$Y_{nt}^* = Y_{nt} + \varphi_{nt} \quad (1.4)$$

$$X_{nt}^* = X_{nt} + v_{nt} \quad (1.5)$$

Now assume that the measurement errors φ_{nt} and v_{nt} are independent of the true values of the mismeasured variables (i.e. classical measurement error) and of r_{nt} , then, the reduced-form model from equation 1.3 above is given as:

$$Y_{nt}^* = X_{nt}^* \beta + r_{nt}' \delta + \alpha_n + \mu_{nt} \quad (1.6)$$

Where $\mu_{nt} = \epsilon_{nt} + \varphi_{nt} - v_{nt} \beta$. It is obvious that X_{nt}^* is endogenous (i.e. correlated with v_{nt}) even if X_{nt} is not. To capture the issue of correlated measurement error, let us suppose that the measurement error φ_{nt} of Y_{nt}^* is given as $\varphi_{nt} = \theta v_{nt} + \epsilon_{nt}$, which implies that $\mu_{nt} = \epsilon_{nt} + \epsilon_{nt} + v_{nt}(\theta - \beta)$. Assume further that ϵ_{nt} and ϵ_{nt} are idiosyncratic errors for X_{nt}^* and φ_{nt} , respectively, and they are not correlated to each other. Then, the only source of bias is via the correlation of X_{nt}^* with v_{nt} ; this can clearly be seen from equation 1.5. Hence, even though by assumption X_{nt} and v_{nt} are not correlated, the correlation between X_{nt}^* (i.e. per capita expenditure) and v_{nt} (i.e. measurement error) makes panel OLS estimation of equation 1.6 inconsistent. Therefore, by instrumenting the term $v_{nt}(\theta - \beta)$, we can consistently estimate equation 1.6.

A standard way to address the outlined endogeneity problem is to use instrumental variable methods where the endogenous regressor is instrumented with a variable such as income that is assumed to be exogenous (like in [Gibson and Rozelle, 2002](#)). In our case, such standard instruments are not available. However, even if standard external instruments are hard to come by, one can use internally generated instruments to identify such models. This was first highlighted by [Griliches and Hausman \(1986\)](#), who showed that a series of error-in-variables models could be identified in a panel data framework without the need for external instruments.

Meijer et al. (2017) suggest three approaches that rely on GMM estimated moment-based conditions with different assumptions: restrictions on the intertemporal matrix of covariance errors of the model, third-moment restrictions, and heteroskedasticity restrictions. In this study, we apply the last method, which was first introduced by Lewbel (2012). He argued that it is an ideal identification method in situations where ordinary instruments are not available. Meijer et al. (2017) have provided a general account of how such an approach could be implemented in a panel data model. In particular, they have shown information from exogenous variables in different time periods as well as their relationship with the endogenous variable can be used to identify mismeasured regressors. Next, we briefly discuss this approach (For details regarding the method, see Meijer et al., 2017).

Suppose r_n contains exogenous – i.e. not mismeasured – variables that are mutually independent of v_n and ϵ_n , then, we can use the relationship between r_n in different time periods with X_n^* to identify the structural model. Meijer et al. (2017) have shown that this can be done when the relationship between r_n and X_n^* is heteroskedastic, an observation first made by Lewbel (2012) for a cross-sectional data context. Suppose a linear relationship between X_n and r_n is as follows:

$$X_n = r_n\kappa + \omega_n \tag{1.7}$$

with $q_n \equiv v_{nt} + \omega_n$, then from equation 1.5 it implies that $X_n^* = r_n\kappa + q_n$. Assume the relationship between X_n^* and r_n is heteroskedastic (i.e. $\mathbb{E}(q_n q_n' | r_n) \neq 0$). If we assume further that $\mathbb{E}(q_n | r_n) = 0$ and $\mathbb{E}(\mu_n | r_n) = 0$, then, any instrument Z_n such that $\mathbb{E}(Z_n' \mu_n) = 0$ also involves satisfying the other two moment conditions (particularly, that r_n and v_n are independent) implies that $Z_n = r_n' q_n$ can be used to consistently identify β and δ . Therefore, if q_n was observable, the use of Z_n as an instrument for identification would be straightforward, but it is unobservable. However, it can be replaced by its estimates \hat{q}_n , which is obtained from the regression of X_n^* on r_n . The generated instruments from this procedure can be used to get consistent estimates for models with mismeasured regressors. our case of mismeasured m , Z_n is a generated instrument and can be used to consistently identify the model.

We follow the recommendation of [Lewbel \(2012\)](#) to include the number of assets owned by the household, mean community nonfood expenditure, age of the household head, education level of the household head, and gender of the household head as variables in r_n that can be used to generate the internal instruments. For these variables to be valid variables for identification, their relationship with X_{nt}^* should be heteroskedastic.

In line with [Meijer et al. \(2017\)](#), we proceed as follows to generate the instruments: First, for each period given as $t = 1, 2, 3$, we regress X_{nt}^* on r_{ns} , $s = 1, 2, 3$; i.e for each time period, the endogenous regressor in that time period is regressed on values of the exogenous regressors in all time period (i.e. r_{n1} , r_{n2} , and r_{n3}). Second, for each of the three regressions in step one, we generate the residual \hat{q}_{nt} . Third, we generate (T=3) set of instruments of z_{nt} (i.e z_{n1} ; z_{n2} ; z_{n3}) from the product $r_{nt}\hat{q}_{nt}$; this leaves us with a total of fifteen generated instruments (five instruments in each time period). Finally, we perform a panel IV estimation with the generated instruments. Note that when the data is transformed into a panel structure, the dimension of the instruments reduces from fifteen to five. Our panel IV model is thus over-identified. We apply the Sargan-Hansen test to check for over-identification as an indication of the validity of the instruments.

Note that this procedure leads to consistent estimation only when measurement error is the only source of endogeneity. Thus, the estimates might not be consistent under the presence of simultaneity bias. In this regard, we check for sensitivity of the results from this approach to the presence of simultaneity bias by combining the generated instruments with the standard or baseline instrument (locality mean non-food expenditure). Given that the computation of this instrument does not involve data on total food consumption, it cannot be a source of common measurement error. For a similar reason, the instrument does not suffer from the problem of reverse causality. [Skoufias et al. \(2009\)](#) also argued in favour of the exogeneity of the instrument. In this regard, the instrument can be considered to be freed from both the reverse causality and correlated measurement error problem, which justifies using it as a baseline instrument.

Apart from measurement error, another problem that might affect the identification of the elasticity parameter β is endogeneity due to simultaneity bias. Specifically, it might be the case that the direction of causation between caloric or nutrient intake and household wealth occurs in both directions, i.e. higher intake of calories or nutrients leads to more productivity due to better health and this, in turn, can cause higher wealth (Skoufias et al., 2011). To address this problem, we follow Skoufias et al. (2011) and instrument total expenditure with mean locality household nonfood expenditure, computed at the household level by excluding each n th household at a time, via a standard panel data instrumental variable technique. As argued in the preceding paragraph, the instrument does not suffer from both reverse causality and correlated measurement error problem.

1.3.2 Non-Linearity

As discussed above, previous research has shown that nonlinearities in the relationship between calories or nutrients and income might also affect the elasticity parameters of interest. To address this issue, we use a semi-parametric panel data model. Among the different classes of semi-parametric models suggested in the literature (See Yatchew, 1998), we choose Baltagi and Li (2002) variant of the partial-linear model. This model allows us to capture nonlinearity in the relationship between nutrient or caloric intake and wellbeing while at the same time making it possible to parametrically include other variables other than wellbeing that might affect caloric or nutrient intake.

Conceptual Framework

The model we estimate can be specified as follows:

$$y_{nt} = r_{nt}'\gamma + g(x_{nt})\theta + u_{nt} \quad (1.8)$$

where y_{nt} denotes the energy, macronutrient or micro-nutrients index variable for household n in year t ; r_{nt} represents a vector of other exogenous time variant characteristics of household n in period t ; $g(x_{nt})$ is a non-parametric function of

per-capita household wealth for household n in period t ; it captures possible non-linearities in the relationship between Y_{nt} and x_{nt} ; u_{nt} is a one-way error component disturbance given as $u_{nt} = \mu_n + v_{nt}$; μ_n denotes household time-invariant fixed effects and v_{nt} is a random component that is assumed to follow a normal distribution.

To estimate the model, we first perform first-differencing to eliminate the household fixed effects, μ_n . Hence, we have:

$$Y_{nt} = R_{nt}\gamma + G(x_{nt}, x_{nt-1})\theta + U_{nt} \quad (1.9)$$

Where $Y_{nt} = y_{nt} - y_{nt-1}$, $R_{nt} = r_{nt} - r_{nt-1}$, $G(x_{nt}, x_{nt-1}) = g(x_{nt}) - g(x_{nt-1})$, and $U_{nt} = u_{nt} - u_{nt-1}$. In estimating γ and θ , we follow [Baltagi and Li \(2002\)](#) and use a series-based method. This method avoids two shortcomings that are associated with the alternative kernel-based method suggested by [Li and Stengos \(1996\)](#), namely: (1) the fact that first-differencing increases the dimension of the problem (curse-of-dimensionality problem); and (2) the fact that it cannot be used to get the original non-parametric function of interest $g(x_{nt})$. We proceed by using a series of the form $p^{k(x)}$ with dimension $K \times 1$ to approximate $g(x)$. If $p^{k(x)}$ can approximate any function in $g \in \mathcal{G}$ as K grows, then, $p^{k(x)}$ can approximate $g(x)$ and $p^k(x_{nt} - x_{nt-1}) = p^k(x_{nt}) - p^k(x_{nt-1})$ can approximate $G(x_{nt}, x_{nt-1})$, where $p^{k(x)}$ are the first k terms of a sequence of functions $(p_{1(x)}, p_{2(x)}, \dots, p_{k(x)})$. Hence, equation 1.9 can be re-written as:

$$y_{nt} - y_{nt-1} = (r_{nt} - r_{nt-1})\gamma + (p^k(x_{nt}) - p^k(x_{nt-1}))\theta + u_{nt} - u_{nt-1} \quad (1.10)$$

Thus, the series term adds an additive structure to the problem. OLS estimates of γ and θ from equation 1.10 are consistent. Note, however, this is true if and only if x_n is exogenous, i.e. it does not suffer from the reverse causality and measurement error problems discussed in preceding section. Hence, if x_n is not exogenous, then, the estimation of equation 1.10 via panel OLS leads to bias point estimates for θ . But if one assumes that the bias due to the endogeneity of x_{nt} does not change over the support of x_{nt} , then, the function $p^k(x_n)$ might not be bias even though the point estimates are bias; this allows us to comment on the behaviour of the nonparametric

estimates despite a possible bias in the point estimates.

Having estimated θ and γ , we follow [Libois and Verardi \(2013\)](#) and use equation 1.8 to fit the fixed effects term of the model, get an estimate of the disturbance term residual, $\hat{\mu}_{nt}$, and then estimate the non-parametric term using standard nonparametric regression techniques. An important consideration in estimating the model is to select the right series for p^k , which can be considered as a spline. A particular kind of splines called B-splines are used; such splines avoids the problem of high correlation between successive terms associated with linear splines. For details regarding this procedure (See [Newson, 2000](#)).

1.4 Results

Our findings from the parametric estimations are reported in Table 1.5. As a baseline, column 1 shows the results from a fixed effects model that is estimated using the within estimator, i.e. assuming that individual specific unobserved effects are not independent of observed covariates.² Extensions of the baseline model to account for simultaneity bias and measurement error, as discussed in section 1.3.1, are reported, respectively, in columns 2 and 3 of Table 1.5. While the IV model for addressing simultaneity bias is exactly identified, the IV model for addressing measurement error is over-identified. Hence, in the latter case, we checked for over-identifying restrictions - that is the validity of instruments - using the Hansen-Sargan test; the p-values from the test are also reported in the table. Each of the nutrient-elasticity estimates shown in Table 1.5 was obtained controlling for other observable characteristics at the household and village level as discussed in Section 1.2. The results for the control variables are not reported here but can be made available upon request. Note that for the model estimated with the generated instruments used as IVs, before generating the instruments, it is important to check whether the relationship between the exogenous and endogenous variables is heteroskedastic. To check for this, we did scatter plots of the generated instruments and the endogenous regressor; the results are reported in appendix A. All the scatterplots indicate the presence of a

² We checked for the validity of the assumption by doing a Hausman test that compares this estimator with the FGLS estimator of an error component model. The results, not reported, indicate that non-randomness of the unobserved effect cannot be rejected; hence, a fixed effect model is a valid specification. Besides, the F test indicated that the within estimator is preferred over the between estimator.

heteroskedastic relationship, which imply that the relationship between the exogenous and endogenous variables can be used to identify the model with measurement error.

The results from the panel OLS estimation show that the calorie total expenditure elasticity in the OVC households is about 0.49, and highly statistically significant. This implies that for every percentage increase in wealth, expressed here in terms of log per capita expenditure, these households increase their intake of calories by about 49 percentage points. If we control for a possible simultaneity bias, we obtain a lower calorie-expenditure elasticity of about 0.39. The calorie elasticity decreases further to about 0.19 when measurement error is addressed using generated instruments from the [Meijer et al. \(2017\)](#) approach.³ Thus, the fixed-effects estimates exhibit a considerable upward-bias. So, even after accounting for simultaneity and measurement error, the relationship between calorie intakes and per-capita expenditure remains positive and statistically significant. A similar pattern holds for the majority of nutrients, with some notable exceptions: first, the intake of two macronutrients – fat and fibre – are found to be unresponsive to changes in per-capita expenditures in the IV regression with generated instruments. Second, the elasticities for vitamin A and D, as well as calcium, rise relative to the fixed-effects model when simultaneity bias or measurement error is addressed. Overall, elasticities of nutrients tend to be higher than the elasticity of calories, which points to a tendency among households to switch to food richer in nutrients as their wealth rises. With an expenditure elasticity of above unity, calcium and vitamin A stand out in this regard.

Tests for weak instruments in the model identified via generated instruments are reported in Table 1.6. The F-statistics in all the nutrient elasticity estimations are above the recommended rule of thumb value of 10 by [Staiger and Stock \(1994\)](#), which indicates that the instruments are relevant for identifying the model under measurement error. However, given that this rule of thumb is not always sufficient, an alternative test for weak instruments suggested by [Stock and Yogo \(2002\)](#) is based on the Cragg-Donald (CD) statistic and they provided the relevant critical values of the test. Since we are using five external instruments to identify a single endogenous regressor, allowing for 5 per cent maximal IV bias means that the relevant CD critical

³ With a p-value of 0.435, the Hansen-Sargan test indicates that the model is over-identified.

TABLE 1.5: Nutrient Income Elasticity from Panel Regressions

	FE	IV	Hetero	IVHetero
Calorie	0.485(0.0145) ^{***}	0.387(0.0478) ^{***}	0.188(0.0698) ^{***}	0.331(0.0594) ^{***}
			[0.435]	[0.157]
price of calorie	0.516(0.0133) ^{***}	0.647(0.0437) ^{***}	0.648(0.0651) ^{***}	0.812(0.0493) ^{***}
			[0.020]	[0.044]
Protein	0.683(0.0149) ^{***}	0.617(0.0488) ^{***}	0.357(0.0752) ^{***}	0.601(0.0687) ^{***}
			[0.540]	[0.177]
Fat	0.682(0.0199) ^{***}	0.577(0.0691) ^{***}	-0.154(0.1612)	0.535(0.0457) ^{***}
			[.087]	[0.208]
Fiber	0.573(0.0184) ^{***}	0.502(0.0596) ^{***}	0.095(0.1002)	0.482(0.0786) ^{***}
			[0.143]	[0.092]
Iron	0.600(0.0186) ^{***}	0.532(0.0605) ^{***}	0.347(0.1014) ^{***}	0.528(0.0860) ^{***}
			[0.259]	[0.253]
Zinc	0.622(0.0162) ^{***}	0.536(0.0537) ^{***}	0.342(0.0860) ^{***}	0.519(0.0783) ^{***}
			[0.359]	[0.127]
Calcium	1.173(0.0286) ^{***}	1.360(0.0932) ^{***}	1.351(0.1422) ^{***}	1.389(0.0903) ^{***}
			[0.847]	[0.924]
Vitamin A	0.976(0.0583) ^{***}	1.675(0.2122) ^{***}	1.124(0.1985) ^{***}	1.429(0.3025) ^{***}
			[0.431]	[0.747]
Vitamin D	0.497(0.0481) ^{***}	0.095(0.2107)	0.599(0.1593) ^{***}	0.436(0.0968) ^{***}
			[0.400]	[0.807]
Folate	0.810(0.0202) ^{***}	0.756(0.0666) ^{***}	0.437(0.1053) ^{***}	0.690(0.0923) ^{***}
			[0.094]	[0.410]
Arginine	0.715(0.0202) ^{***}	0.650(0.0688) ^{***}	0.540(0.1088) ^{***}	0.689(0.1861) ^{***}
			[0.494]	[0.267]
Histidine	0.710(0.0156) ^{***}	0.605(0.0530) ^{***}	0.432(0.592) ^{***}	0.563(0.0643) ^{***}
			[0.0827]	[0.323]
Lysine	0.847(0.0170) ^{***}	0.733(0.0563) ^{***}	0.530(.0877) ^{***}	0.807(0.0686) ^{***}
			[0.529]	[0.301]

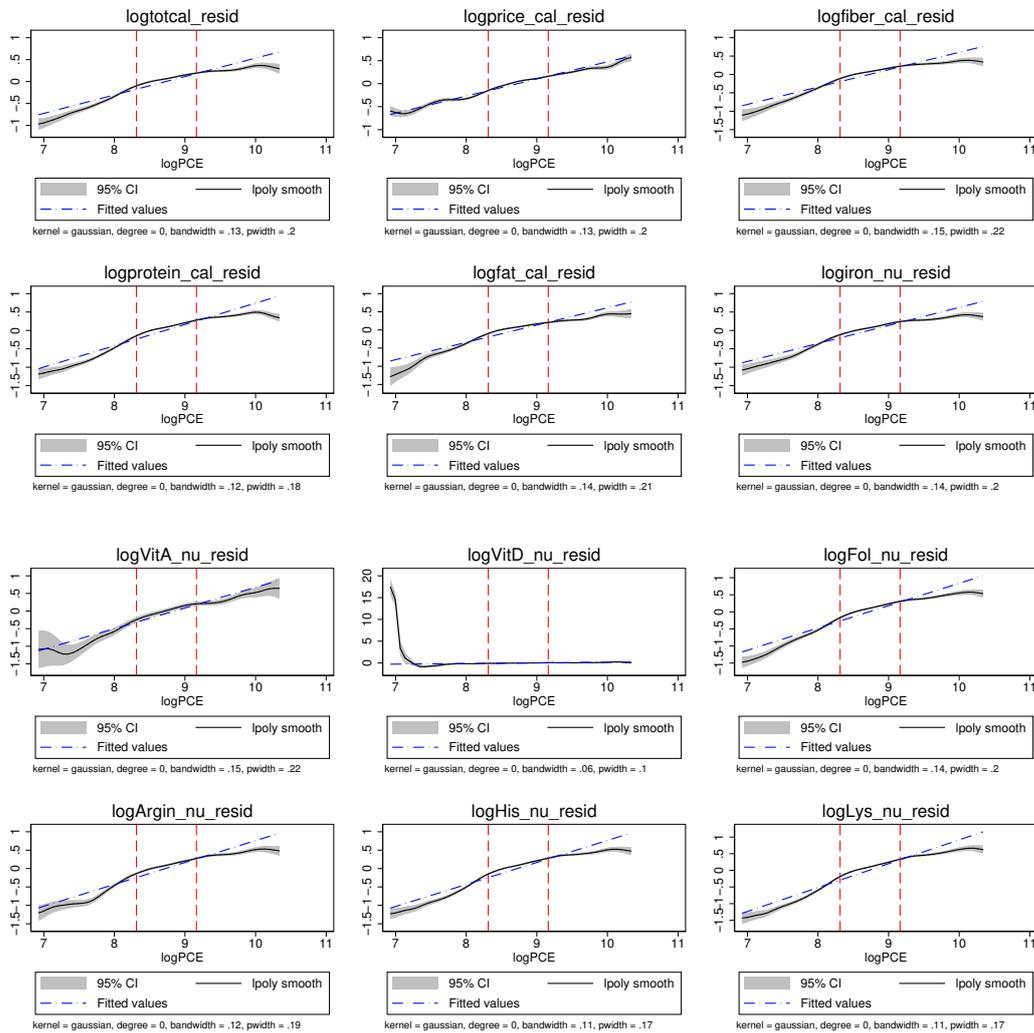
Reported are the estimates of the calorie or nutrient income elasticities from the panel regressions. Note: FE = Estimation results of the panel fixed effects estimated using the estimator; IV= Estimation results from panel instrumental variables with locality mean nonfood expenditure as the only instrument. Hetero= Estimation results from panel instrumental variable model with five generated instruments from heteroskedasticity restrictions; IVHetero= estimation results from panel instrumental variables model with mean locality nonfood expenditure and the five generated instruments; the robust standard errors are reported in the parentheses; In the last two columns, reported in brackets are the p-values from the Hansen-Sargant over-identification tes; fixed effect model is estimated using the within estimator and the overidentified models are estimated using GMM. Significance levels: *** 99% significance; ** 95% significance; *90% significance.

value for us is 18.7. In all the nutrient elasticity estimations, we obtain a CD statistic that is markedly higher than the critical value, which again indicates that our generated instruments IVs do not appear to suffer from a weak instruments problem. The Anderson-Rubin test, p-values shown in the three row of Table 1.6, which are robust against the presence of weak instruments, corroborates the evidence from the CD statistics.

As discussed in section 1.3.1, the generated instruments via the [Meijer et al. \(2017\)](#) method might not be robust against simultaneity bias. To this end, we did a sensitivity analysis of the generated instruments to simultaneity bias by combining them with the baseline instrument, which by construction does not suffer from measurement error bias. The results of this estimation are reported in the last column of Table 1.5. From the estimates, we see that the nutrient elasticity estimates under this column are higher than the previous column, which indicates that using the generated instruments leads to an over-correction of the OLS bias. For per capita calorie intakes for example, the estimates from a model with the combined instruments reports a calorie elasticity of about 0.33, which is close to the calorie elasticity of 0.39 from the panel IV with the baseline instrument than the calorie elasticity of 0.19 from the model with the generated instruments. However, the model with the baseline instrument imply slightly more efficient estimates as the standard errors are a bit smaller. Therefore, the model identified via the standard instruments is overall better. A similar observation can be made from the elasticity estimates of the macro and micro nutrients. In all the elasticity estimates, the test for overidentification using the Sargan-Hansen test are satisfactory. In this regard, the sensitivity analysis results show that the elasticity estimates arrived at using the standard instrument are more reliable. This is not surprising given that the [Meijer et al. \(2017\)](#) instruments corrects for just endogeneity due to measurement error bias.

Now we turn to the results from the semi-parametric model. In line with the discussions above, we estimate the non-parametric component, $g(x_{nt})$, employing a kernel-weighted local polynomial regression. For our discussions here, we focus on the fitted curves from the estimations reported in Figure 1.1, which shows how the various nutrients relate to log per-capita expenditure. The blue dotted line on each graph represent a linear fit of the main regression function. The two vertical

FIGURE 1.1: Nonparametric Estimation Results



Partial linear model estimation of the relationship between calorie or nutrient and per capita expenditure. The shaded areas on the graphs are the 95% confidence bands. The first and second red dashed vertical lines represent, respectively, the bottom and top quartile of per capita expenditure. The dotted blue lines are linear fits of the main model, which shows how the nonparametric representation deviates from linearity.

dotted lines represent the bottom and top quartile of per capita total expenditure, respectively. For details regarding the relationship between nutrients intake and the other household characteristics, see Table A.1; given that the point estimates of the partial linear models might be bias, these results should be viewed with care.

We find that per-capita calorie intake increases monotonically with log per-capita expenditure, but the growth rate slows down at higher levels of expenditure, which implies that with the same growth in expenditure, the increase in calorie intake is

lower at higher expenditure levels. This result is consistent with previous studies (e.g. [Behrman and Deolalikar, 1987](#); [Tian and Yu, 2015](#)). In addition, when we compare the linear fit to the nonparametric fit of the nutrient elasticity estimate, we see for the case of calories a statistically significant deviations from linearity at higher per capita expenditure levels; this reinforces the finding that the elasticity of calorie intakes, even for ultrapoor households, differs between poor and rich households. In terms of economic significance, the deviation from linearity is not that sizable; for calories, it is about 0.025 at log per capita expenditure of 10. Food quality as measured by the price of calories also increases continuously with per-capita expenditures of the OVC households, with one notable exception: at very low levels of expenditure, an increase in expenditure is associated with a statistically significant decline in food quality of up to 20% before it starts to increase. This is in contrast to what [Skoufias et al. \(2011\)](#) found for poor households in Mexico. The growing part of the curve is steepest at very high expenditure levels, i.e. at the upper tail, where the elasticity of food quality for per-capita expenditure is highest. ⁴

The general pattern that emerges for per-capita calories also holds for most nutrients. The intake of all macronutrients considered here (fibre, protein, and fat) increase with higher per-capita expenditures. As shown by the vertical dashed lines in the graphs, the macronutrients' responsiveness is stronger for per-capita expenditures in the bottom quartile in the top quartile. Likewise, except vitamin D, for which the curve first declines and then flattens, micronutrient intake increases as per-capita expenditure rises, the slope of the curves being somewhat flatter for households in the top quartile than for households in the bottom quartile. Furthermore, in all the graphs, we see statistically significant deviations from linearity at higher per capita expenditure levels. Therefore, even though calories or nutrients tend to generally increase with wealth, the rate of increase is more pronounced for poorer households than it is for richer households. In terms, of magnitudes the deviations do not seem that sizeable.

Overall, all graphs in Figure 1.1 points to a non-linear relationship between caloric and nutrition indices and log per-capita expenditure that our nonparametric model

⁴Note that the confidence bands tend to be wider at the tails. This implies less precise estimates, which is likely to be due to the presence of fewer households.

TABLE 1.6: IV/GMM Estimation Test Statistics

	Calorie	Price calorie	Protein	Fat	Fiber	Iron	Zinc	Calcium	Vit. A	Vit. D	Folate	Arginine	Histine	Lysine
F-stats	19.4	15.88	15.10	15.43	15.43	15.43	15.32	15.43	16.79	12.48	15.34	15.32	15.32	15.32
CD-stats ⁺	34.05	28.56	27.09	27.58	27.58	27.58	27.41	27.58	24.72	26.02	27.42	27.41	27.41	27.41
AR	0.090	0.000	0.160	0.008	0.078	0.017	0.011	0.000	0.000	0.005	0.002	0.003	0.002	0.000
Endo	0.000	0.134	0.000	0.000	0.000	0.007	0.001	0.192	0.472	0.489	0.001	0.085	0.001	0.000

Various test of instrument validity from the panel IV estimation of the model with generated instruments. The statistics are reported for each nutrient elasticity as well as the elasticity of the price of calorie. Note: 1 Since we are insrumenting one endogeneous variable with five external instruments, the applicable Stock-Yogo critical value at 5% maximal IV relative bias is 18.37. Therefore, the Cragg Donald statistics should be compared with this critical value. 2. F-start= first stage F-statistics; CD= Cragg-Donald Statistics; AR=Anderson Robin test p-value; Endo= P-values for Endogeneity test.

captures better.

1.5 Summary and Conclusion

Despite large existing literature, the issue of whether and to what extent additional income can help poor households meet their dietary needs is still not fully resolved. In this study, we provide new evidence on calorie-expenditure and nutrient-expenditure elasticities in the so far largely overlooked setting of ultra-poor households in Sub-Saharan Africa. Employing panel data estimation techniques that control for simultaneity and measurement error bias, we find for a sample of close to 1800 Kenyan OVC households that higher per-capita expenditures are generally associated with higher calorie and nutrient intake. Richer OVC households tend to consume food richer in macro and micronutrients than poorer OVC households. Food quality also tends to be better in richer OVC households than in poorer ones. A policy implication of these findings is that social protection schemes such as social assistance in the form of income transfers have the potential to help poor households get access to better diets.

From a methodological point of view, our results suggest that biases resulting from simultaneity and measurement error are considerable, rendering it essential to control for them. We also find that even in extremely poor households there are non-linearities in calorie and nutrient intake, which we accommodate by using a semi-parametric model. A shortcoming of our study is that when accounting for non-linearity we rely on a very restrictive assumption regarding bias due to endogeneity, which we do not account for as models for estimating a partial linear model

where the non-parametric term is endogenous are not yet well developed; thus, this is something we leave for future research.

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Appendices

Appendix A

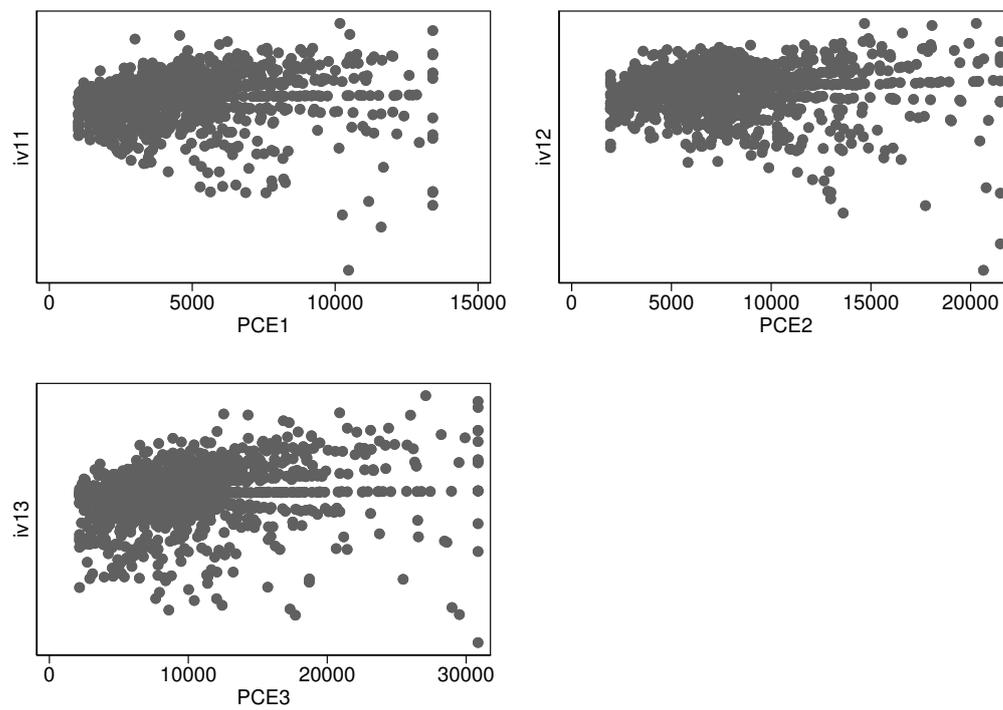
Additional Tables and Figures

TABLE A.1: Other Covariates in the Semi-Parametric Model

	Calorie	Price calorie	Protein	Fat	Fiber	Iron	Zinc	Calcium	Vit. A	Vit. D	Folate	Arginine	Histine	Lysine
Ageh	-0.003** (0.0010)	-0.000 (0.0012)	-0.003 (0.0019)	-0.002 (0.0011)	0.001 (0.0019)	-0.004 (0.0024)	-0.002 (0.0011)	0.000 (0.0020)	-0.014 (0.0140)	-0.002 (0.0060)	-0.004 (0.0021)	-0.002 (0.0017)	-0.001 (0.0011)	-0.001 (0.0010)
Fehead	0.032 (0.0503)	0.016 (0.0272)	0.046 (0.0544)	0.037 (0.0452)	0.047 (0.0655)	0.039 (0.0625)	0.037 (0.0625)	-0.092 (0.0883)	0.209 (0.1551)	-0.013 (0.1711)	0.036 (0.0322)	0.070 (0.0722)	0.040 (0.0519)	0.027 (0.0387)
Eduthead	0.019 (0.0244)	-0.054 (0.0231)	0.066 (0.0434)	0.011 (0.0271)	-0.039 (0.0478)	0.069 (0.0610)	0.022 (0.0339)	-0.081* (0.0348)	0.209 (0.2563)	-0.053 (0.1142)	0.019 (0.0578)	0.026 (0.0354)	0.007 (0.0259)	-0.024 (0.0316)
Loghwszize	-0.320*** (0.0491)	0.091 (0.0785)	-0.227*** (0.0471)	-0.241*** (0.0434)	-0.459*** (0.0701)	-0.229** (0.0631)	-0.238*** (0.0430)	-0.215*** (0.0537)	0.039 (0.2600)	-0.542*** (0.1241)	-0.216* (0.0914)	-0.179*** (0.0443)	-0.216*** (0.0236)	-0.213*** (0.0509)
Childu6p	0.150 (0.0876)	-0.4122*** (0.0482)	-0.066 (0.1509)	-0.013 (0.1264)	0.145 (0.1550)	-0.071 (0.1426)	0.017 (0.1346)	0.120 (0.1146)	-0.553 (0.5406)	0.714 (0.4070)	-0.131 (0.2359)	-0.054 (0.1235)	0.046 (0.0971)	0.001 (0.1113)
Childu14p	0.026 (0.0924)	-0.097 (0.0953)	-0.096 (0.1421)	0.060 (0.0938)	0.367** (0.1356)	-0.094 (0.1470)	-0.005 (0.1080)	0.337*** (0.0820)	-0.377 (0.5318)	0.713*** (0.1553)	-0.072 (0.1924)	0.041 (0.0928)	0.042 (0.0708)	0.107 (0.0705)
Teemp	-0.669*** (0.1697)	0.484** (0.1867)	-0.9141*** (0.2109)	-0.457** (0.1479)	0.373 (0.2890)	-0.884*** (0.2163)	-0.646** (0.1820)	0.564* (0.2368)	-0.882 (0.8840)	1.753*** (0.2691)	-0.790** (0.2807)	-0.461* (0.2018)	-0.407** (0.1220)	-0.111 (0.1059)
Road	0.071 (0.0434)	0.051 (0.0724)	0.103* (0.0430)	0.092* (0.0458)	0.029 (0.0476)	0.141** (0.0472)	0.095* (0.0420)	-0.042 (0.1419)	0.851** (0.3088)	-0.087 (0.0527)	0.125 (0.0651)	0.069 (0.0459)	0.067* (0.0324)	0.034 (0.0383)
Market	0.000 (0.0005)	0.000 (0.0007)	0.000 (0.0005)	0.000 (0.0005)	0.001 (0.0013)	0.000 (0.0005)	0.000 (0.0005)	-0.000 (0.0006)	0.003 (0.0017)	0.001 (0.0014)	-0.000 (0.0010)	0.000 (0.0006)	0.000 (0.0004)	0.000 (0.0006)
R-sq	0.33	0.13	0.29	0.35	0.21	0.29	0.31	0.17	0.13	0.10	0.31	0.25	0.34	0.32
N	2982	3080	3067	3084	3084	3084	3083	3084	1695	944	3081	3083	3083	3083

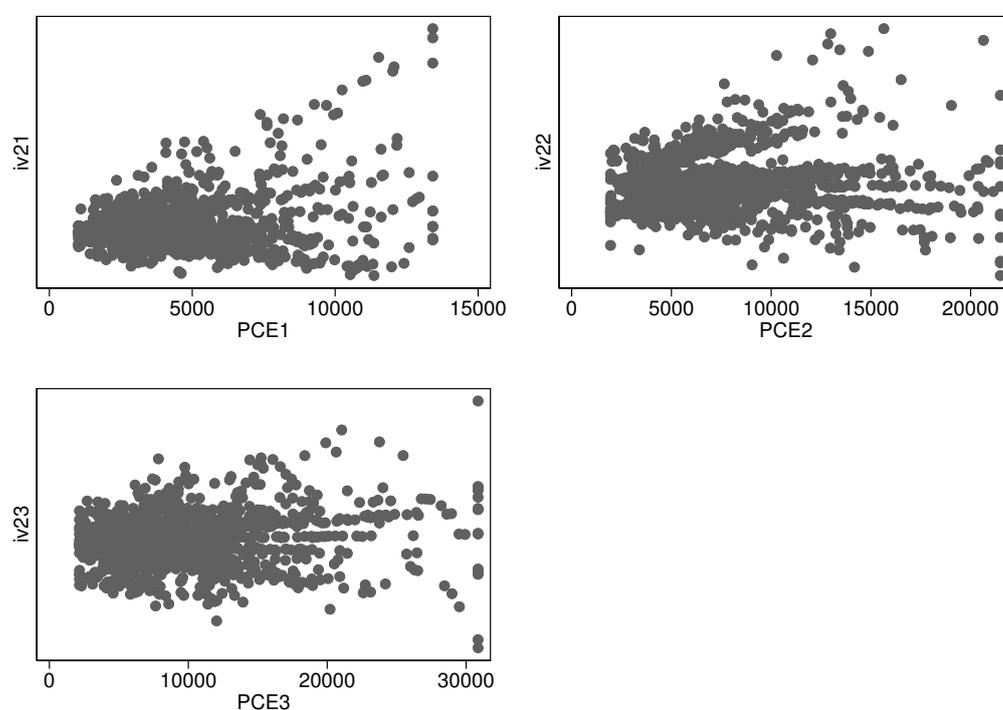
The estimates of the of the coefficient of the variables that enter parametrically in the partial linear model of each nutrient. Note: Reported in parantheses are the robust standard errors; R-sq=Adjusted within R-squared; N=number of observations used in the estimation. Level of significance: *** 99%; ** 95%; *90%.

FIGURE A.1: Scatterplot: Asset Ownership



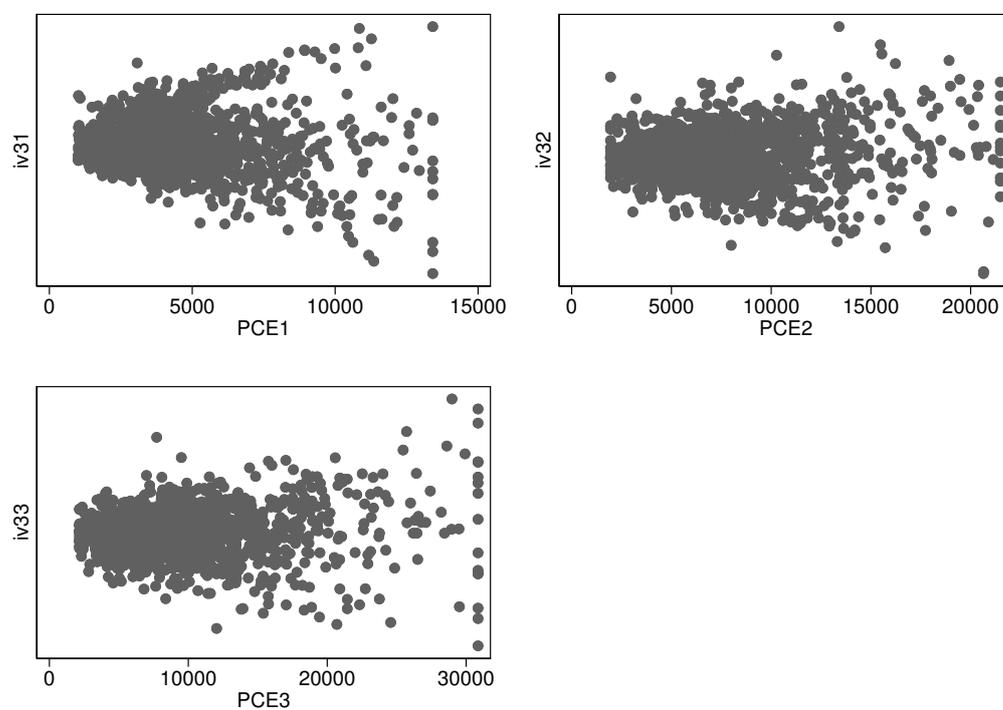
Graph shows scatterplots of the generated instrumental variables (on vertical axis) and the endogenous regressor (PCE_{nt} , $t = 1, 2, 3$). $iv1t$ = generated instrument from asset ownership (i.e. r_{nt}) in period t , $t = 1, 2, 3$, PCE= Per Capita Expenditure.

FIGURE A.2: Scatterplot: Mean Nonfood Expenditure



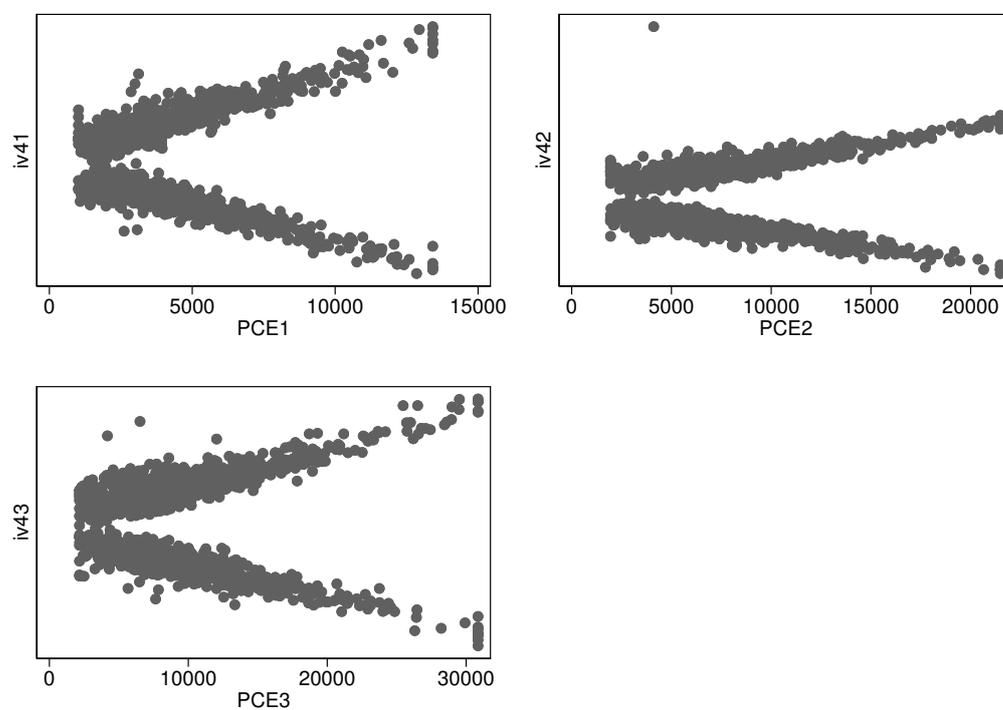
Graph shows scatterplots of the generated instrumental variables (on vertical axis) and the endogenous regressor (PCE_{nt} , $t = 1, 2, 3$). $iv2t$ = generated instrument from mean nonfood expenditure (i.e. r_{n2t}) in period t , $t = 1, 2, 3$, PCE= Per Capita Expenditure.

FIGURE A.3: Scatterplot: Age of the Household Head



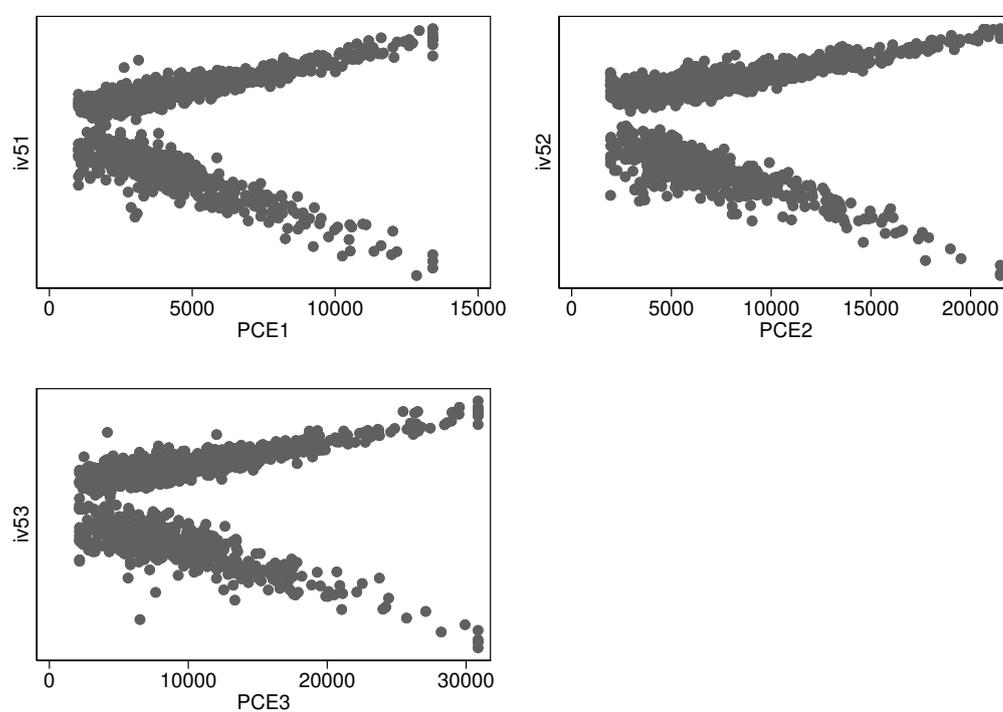
Graph shows scatterplots of the generated instrumental variables (on vertical axis) and the endogenous regressor (PCE_{nt} , $t = 1, 2, 3$). $iv3t$ = generated instrument from age of the household head (i.e. r_{n3t}) in period t , $t = 1, 2, 3$, PCE= Per Capita Expenditure.

FIGURE A.4: Scatterplot: Education Status of the Household Head



Graph shows scatterplots of the generated instrumental variables (on vertical axis) and the endogenous regressor (PCE_{nt} , $t = 1, 2, 3$). $iv4t$ = generated instrument from education status of the household head (i.e. r_{n4t}) in period t , $t = 1, 2, 3$, PCE= Per Capita Expenditure.

FIGURE A.5: Scatterplot: Gender of the Household Head



Graph shows scatterplots of the generated instrumental variables (on vertical axis) and the endogenous regressor (PCE_{nt} , $t = 1, 2, 3$). $iv5t$ = generated instrument from gender of the household head (i.e. r_{n5t}) in period t , $t = 1, 2, 3$, PCE= Per Capita Expenditure.

Chapter 2

Access to Formal Savings and Household Welfare: Evidence from Gambia

2.1 Introduction

Despite much progress being made in the fight against poverty, poverty continues to be a bottleneck; between 1990 and 2013, the world has witnessed a remarkable decline in poverty – about 35 percent according to reports by the World Bank. However yet still many people, especially in Sub-Saharan Africa (SSA), continue to be poor; about 330 million people in the region live below the poverty line of \$1.90 per day (Beegle et al., 2016). One intervention that can be effective in bringing economic prosperity to the poor in this region is financial inclusion (FI). Evidence has shown that access to financial services like saving has the potential to spur economic development and growth by facilitating consumption smoothing, helping in capital accumulation, and investment in health and education (Pande, 2012). Given that lack of access to finance can be a source of persistent inequality (See Banerjee and Newman, 1993), financial inclusion can also promote inclusive economic development through social equity (Beck et al., 2007).

However, in developing countries, especially fragile and conflict-affected countries in SSA, access to financial services like formal savings is still low. According to the Global Findex report 2017 by Demirgüç-Kunt et al. (2017), only 27 percent of adults in these places have a regular account. Even though smart technologies like

mobile money are revolutionising formal account access in low-income countries, overall the gains have been modest [Demirgüç-Kunt et al. \(2017\)](#). The low access rate of formal financial services in developing countries can be explained by both demand and supply side constraints ([Karlan et al., 2014](#)). On the supply side, factors such as high transaction cost, lack of trust of financial institutions, and regulatory restrictions make it harder for the poor to access saving products. On the demand side, factors such as low financial literacy, lack of motivation to hold accounts, social constraint, and behavioural biases have been cited as factors that inhibit access to formal financial services. Hence, these factors can limit the ability of formal saving providers to act as a catalyst to economic growth ([Pande, 2012](#)).

Thus, there has been a surge in interest among development economist and practitioners to understand how the easing of the highlighted constraints could help the poor to access more saving products, and consequently whether access to such products contributes to economic development by generating downstream effects on the wellbeing of the poor. Most of the evidence that exists thus far, though still scanty and inconclusive, suggest that financial inclusion through saving has the potential to improve welfare. In particular, evidence has shown that access to financial services (both saving and credit) can help households to address risk associated with consumption (See [Dupas and Robinson, 2013b](#); [Jack and Suri, 2014](#)), enhance food security in recipient households (See [Dupas et al., 2017](#)), empower women ([Ashraf et al., 2010](#)), and also boost entrepreneurship development among women ([Dupas and Robinson, 2013a](#)). In a recent systematic review of the existing evidence in SSA via a meta-analysis, [Steinert et al. \(2018\)](#) find that “saving promotions” can generate a positive impact on poverty reduction by increasing household welfare, increasing returns from private entrepreneurship, and enhancing food security. Similar evidence is reported by [Pande \(2012\)](#).

Therefore, the existing evidence, albeit limited, has motivated an emergence of what appears to be a consensus that it is possible for access to formal saving to produce positive welfare impact on households thereby promoting inclusive economic growth and development. This insurgence of evidence has made the promotion of saving a foci part of the global agenda to promote financial inclusion of the poor as a means for achieving the 2030 Agenda; the G-20 Financial Inclusion Action Plan and

the Maya Declaration championed by the Alliance for Financial Inclusion (AFI) are examples of such global initiatives.

Regarding why access to saving might improve household welfare, researchers have suggested three central pathways through which this happens (Steinert et al., 2018): Firstly, saving motivates households to make a higher investment into assets that enhance longterm wellbeing. Secondly, access to saving can act as a buffer against unforeseen economic shocks. Thirdly, saving products help holders to deal with self-control problems and other behavioural shortcomings.

Despite the empirical evidence on access to saving increasing significantly in recent years, it is still limited when compared to other aspects of financial inclusion such as access to credit (Cull et al., 2014). Furthermore, when it comes to Sub-Saharan Africa, where most of the evidence is based, much attention is paid to few countries such as Kenya and Uganda (See Sabet and Brown, 2018). Thus, not much specific evidence exists for other countries whose agents face different economic realities. Hence, understanding the impact of saving from a perspective different from these countries should be an addition to the literature; especially considering that experimental results are usually very context dependent. Furthermore, the evidence on the impact of access to saving products on household welfare is still limited (Steinert et al., 2018). One reason for this might be that in experimental studies, where most of the rigorous evidence is found, the ability to provide precise estimates of downstream effects on outcomes such as education or health spending or business investment depends not only on take-up rates but also usage rates. If the latter is low, it makes it challenging to ascertain the precise impact of the innovations on well-being; for example, in Dupas et al. (2018) this was raised as a potential issue.

Therefore, the central motivation of this paper is to contribute to the literature from the perspective of the issues above regarding welfare impacts of access to formal savings. Specifically, I want to add to the scanty evidence of the effects of saving on household well-being; especially, on indicators such as consumption, education spending, and asset ownership. Although the evidence on the welfare impact of saving on these outcomes has been increasing, as discussed above, it is still limited when compared to other areas of financial inclusion such as access to credit. Hence, this is a limitation as a lack of sufficient evidence makes the implementation of strategic

reviews with enough power tricky, which consequently affects the extent to which results can be given a general perspective. Therefore, more empirical evidence will help in this regard. Another aim of the study is to provide rigorous evidence on the impact of access to formal saving on household welfare in Gambia. Like many developing countries, access to formal saving in Gambia is very low. According to [Jaabi \(2017\)](#), more than 70 per cent of the population in Gambia are financially excluded, and only about 16 per cent hold bank accounts. Thus, the promotion of financial inclusion, especially access to basic saving accounts that could be a means to more access of other financial services such as credit, is part of the government's agenda to boost inclusive economic development and growth in Gambia. However, until now no rigorous evidence exists on whether access to formal saving can contribute to poverty reduction in Gambia. Thus, this study also aims at adding to the filling of these gaps.

To this effect, I use quasi-experimental causal inference methods to study the impact of access to financial services on household welfare in Gambia. Specifically, a propensity score matching with kernel ridge regression and doubly robust causal inference methods are used to evaluate the impact of formal saving on household outcomes such as education spending, health spending, food consumption, asset ownership, and total expenditure. The data I use come from Gambia Integrated Household Survey (IHS) 2015/16, which is a representative nationwide household survey conducted by Gambia Bureau of Statistics with some financial and technical assistance from the World Bank under the Capacity Building and Economic Management Project (CBEMP).

The results indicate that access to formal saving has a positive and significant effect on households' consumption as it increases monthly per capita total expenditure and food expenditure. It also increases annual per capita education expenditure up to 72% as well as asset ownership. Furthermore, I find that access to formal saving has positive but no significant impact on household's out-of-pocket per capita health expenditure. To gauge the robustness of the results against alternative specifications and unobserved confounders, I also estimated the average treatment effects using a doubly robust estimator and did sensitivity analysis using the approach of [Rosenbaum \(2002\)](#); respectively. I obtained that the results from the propensity score

matching model using kernel ridge matching are similar to those from the doubly robust model. Also, I find that while the results for food expenditure and asset ownership are not sensitive to mild hidden bias the results on education and food spending are susceptible to mild hidden bias. Thus, taking together I argue that the most robust impact holds for total expenditure and asset ownership. The effect size I get on these indicators is similar to some found in the experimental literature on the same topic (e.g. [Prina, 2015](#)).

The rest of the chapter is organised as follows: Following the introduction, in section 2.2, I give a brief description of the current context regarding financial inclusion in Gambia. Then, the methodological approach is discussed in section 2.3. The data and sample characteristics are addressed in section 2.4. In section 3.6, I present and explain the effect I find. Then, I end with a conclusion in section 3.7.

2.2 Financial Inclusion as a Tool to Enhance Household's Welfare in Gambia

Like many countries in Sub-Saharan Africa (SSA), poverty in Gambia continues to be a challenge. Estimates by Gambia Bureau of Statistics indicate that in 2016 about 49 percent of the population lives in absolute poverty; when compared to the absolute poverty rate in 2010, this implies that between 2010 and 2016 about 150,000 of the people have moved into poverty ([GBOS, 2017](#)). For a country with such high levels of poverty, promotion of financial inclusion via access to formal financial services has the potential to catalyse inclusive economic growth and development thereby moving a lot of people out of poverty. Evidences from other part of the world (See [Ashraf et al., 2010](#); [Bruhn and Love, 2014](#), for a review) have shown that access to formal financial services help households to set aside money to handle lump-sum expenditures (such as education expenditures, agricultural expenditures, and health investment) and accommodate unexpected income shocks, which reduces both poverty and income inequality. It is against this backdrop that financial inclusion is heralded as an essential tool to stimulate the achievement of the sustainable development goals (SDGs); it has been identified to be an enabler for 7 out of the 17 SDGs ([World Bank, 2018](#)). Consequently, the promotion of financial inclusion

as a tool for economic and social development is a crucial goal for many developing countries including Gambia.

In Gambia, despite the proliferation of bank and non-bank financial institution in the past decade, still, a considerable proportion of the population does not have access to formal financial services such as basic savings accounts. My estimates indicate that just about 21% of households in Gambia have access to formal means of saving, which is weigh below the African average of 34% - according to reports in the Global Findex by [Demirgüç-Kunt et al. \(2015\)](#). Despite no precise explanations for the reasons for such low levels of formal financial inclusion, the reasons that explain it could be similar to those reported in the literature (e.g. [Dupas et al., 2018](#)). In particular, among the reasons why many people in developing countries like Gambia are still unbanked are high participation cost, low financial literacy, and lack of trust in financial institutions as well as lack of availability of financial service providers in areas predominantly occupied by the poor. The latter is still a massive challenge in Gambia. Currently, about 12 commercial banks are operating in the country and operate mostly in just urban and peri-urban areas ([Tomaselli et al., 2013](#)); not more than 5 of the 12 commercial banks have branches in rural communities. However, even for those that have branches in rural areas, they serve mainly the large towns in these communities. According to [Sanyang and Huang \(2008\)](#) one reason why commercial banks limit their outreach in urban areas and to formal sector entrepreneurs is weak policy and regulatory environment; in other words, the policy and regulatory environment makes it unattractive for the formal financial sector to extend their services to the poor. Against this backdrop, most households in rural areas access formal financial resources mainly through non-bank financial institutions such as microfinance institutions, credit unions, Village Savings and Credit Associations (VISACAS), and NGO-based microfinance schemes (See [Nagarajan et al., 1994, 1999](#)).

The difficulties in access to formal financial services culminate into low levels of formal account ownership, and this plus weak state-run social protection schemes implies many people uses informal financial resources such Rotating Savings and

Credit Associations (ROSCAS) and traditional money lenders as means for smoothing consumption (Collins et al., 2009). However, such methods of smoothing consumption are known to be both inadequate and expensive (Morduch, 1999). For this reason, it is a commonly held belief that the promotion of access to formal financial services by the poor and in rural areas should be among the core objectives of the Government of The Gambia (Jaabi, 2017). Hence, as part of a broader rural development agenda for poverty alleviation in Gambia, the government promote financial inclusion in rural communities; however, most of the efforts are currently concentrated on increasing financial access for agricultural development.

Regarding the impact of formal financial services, some anecdotal reports and a qualitative study by Sanyang and Huang (2008) have indicated that access to financial resources like formal means of saving or credit produces a positive impact on household welfare. However, until now no rigorous evidence exists to this effect. Therefore, the specific objective of this present study is to provide rigorous evidence on the impact of access to formal savings on household welfare in Gambia. Although many people are still financially excluded, understanding the welfare impacts of access to formal financial services such as formal saving on those that have access to such services is still a significant research undertaking. It will provide a strong case for more policy intervention in this front.

2.3 Methodology

The decision to use a quasi-experimental approach to estimate the impact of saving on well-being in Gambia is motivated by the fact that access to saving by the households in the study was not randomised, hence, the decision to own a formal account could be endogenous. For instance, it could be that households that own saving products are those with better socio-economic status or better in forecasting their future financial needs and therefore set money aside to account for them. If such observe and unobserved factors affect both treatment assignment (here owning a formal saving account) and outcomes, and they are not controlled for, then, the impact of the treatment cannot be interpreted as causal. Hence, a study that relies on such a measure of impact would lack internal validity. One way to deal with

this problem is to use a quasi-experimental evaluation methods (See [Imbens and Wooldridge, 2009](#), for an excellent summary). In particular, one can use matching and regression adjustment methods to find a valid estimate of the missing counterfactual; that is what outcome would have been realised by households with access to formal savings had it been they do not have access to formal saving. In this study, we use this approach to identify treatment effects. Thus, next, I discuss in details the approach.

2.3.1 Conceptual Note

Suppose a household i (where i goes from 1 to N , and N is the sum of all units in the population) is a member of the evaluation sample. The household is either enrolled in a saving intervention or not enrolled. Let the indicator variable denoting enrolment be given as D , which is 1 if the household is a participant in a saving program (in this study, I focus on formal saving, i.e. saving with a formal financial institution) and 0 otherwise. In the framework of the Rubin causal model (discussed in details by [Imbens and Rubin, 2015](#)), suppose the potential outcome associated with each of these two states for the i th household is given as $Y_i(D_i)$, where again $i = 1, 2, \dots, N$ and $D_i = 1$ if the household is participant and $D_i = 0$ if nonparticipant. Let the indicator of treatment status be $T = 0, 1$ with 1 indicating treatment receipt and 0 otherwise. The realised outcome of each household can be represented as:

$$Y_i = (D_i)Y_i(1) - (1 - D_i)Y_i(0) \quad (2.1)$$

Equation 2.1 is also known as the Fisher or Roy Model ([Heckman et al., 1997](#)). Thus, $Y_i = Y_i(1)$ if the household has access to formal saving services and $Y_i = Y_i(0)$ if it does not. One estimand of interest is the average treatment effect of having a saving product for the i th household, which can be represented as:

$$ATE_i = E(Y_i(1)) - E(Y_i(0)) \quad (2.2)$$

Which means that the average treatment effect is given as the average difference in potential outcomes between households with access to saving and households without access to saving. However, in this state, it is clear that there is a problem with this specification as $Y_i(D = 0)$ is not observed for households with a saving product. Similarly, $Y_i(D = 1)$ is not also observed for households without a saving product; it means that the same household cannot be a household with access to saving and a household without access to saving concurrently. In the evaluation literature, this phenomenon is commonly dubbed as the "fundamental problem of causal inference" believed to have been first used in this way by (Holland, 1986). According to Rosenbaum and Rubin (1983) this phenomenon can be seen as a missing observation problem since $Y_i(D = 0)$ and $Y_i(D = 1)$ are, respectively, missing outcomes for participants and nonparticipants. Therefore, the challenge in causal inference is finding a valid estimate of these missing counterfactuals (Cook et al., 2002). For observational studies, five main methods are popularly used: Randomisation, Diff in Diff, instrumental variable (IV), matching methods, and recently regression discontinuity; (See Khandker et al., 2009, for discussion of the first three) and (Van der Klaauw, 2008, for the last one). Another method that is attracting interest in this literature is machine learning (See Athey, 2017)

Although the ATE is one of the main estimands of interest, it is not the only one. Another estimand of interest could be the average treatment effect on the treated (ATT) or the average treatment effect on the non-treated (ATNT) (See Imbens and Wooldridge, 2009). According to Imbens (2004), the decision as to which estimand to use should depend on the problem at hand. In this study, I adopt the ATT as the main estimand of interest as I am interested in ascertaining the causal impact of owning a formal saving product on the welfare of all households that have reported in the survey that they have access to such accounts. The ATT is given as follows:

$$ATT = E(TE|T = 1) = E[Y(1)|T = 1] - E[Y(0)|T = 1] \quad (2.3)$$

Where TE is the treatment effect. When selection bias is present, usually the case in non-experimental settings as here where the assignment to treatment is not random, ATT is not identified; it is, therefore, a bad proxy for the true treatment effect. It

originates from the fact that selection bias creates a difference between the treatment and control group even before the treatment and attaching this to the treatment is misleading (Rosenbaum and Rubin, 1983). As a result, if selection bias cannot be ruled out, further assumptions have to be made on how it should be handled to identify the estimator. As discussed above, several methods are available on how this can be done. In this study, I use matching methods; in particular the propensity score method and inverse probability weighting combined with regression adjustment – so-called Doubly Robust (DR) estimators. As I hinted in the introduction, the DR estimator is used to check for robustness of the PSM estimator; this is in line with recommendations in the evaluation literature to check the robustness of results using alternative estimation methods (e.g. Athey et al., 2017).

Matching is a way of determining treatments effects whereby treated units are paired to untreated units with whom they have the same observable characteristics, and average treatment effects are arrived at by subtracting the average outcome of the non-treated units from the average outcome of treated units (Heckman et al., 1998). Matching relies on two assumptions to identify the treatment effects via estimation of the missing counterfactual: the unconfoundedness assumption and overlap or common support assumption. The first requires that conditional on the observed covariates potential outcomes are independent of treatment assignment, which means treatment is based solely on observables. The second avoids certainty in predictability and therefore requires that units with identical covariates have a non-zero chance of being in either the treatment or control group. The overlap assumption implies that conditional distribution of covariates of units in the treatment group should perfectly overlap with the conditional distribution of covariates of units in the comparison group (Imbens and Wooldridge, 2009). When taking together, these two assumptions are what Rosenbaum and Rubin (1983) called strong ignorability, which when satisfied imply matching estimators identify the same parameters as experiments (Heckman et al., 1997).

Therefore, under matching on observed covariate vector X , the treatment effects can be summarized as:

$$\begin{aligned} ATT &= E(TE|T = 1, X) = E[Y(1)|T = 1, X] - E[Y(0)|T = 1, X] \\ &= E[Y(1) - Y(0)|T = 1, X] \end{aligned} \quad (2.4)$$

PSM Approach

Since matching on each covariate in X is difficult in practice due to the curse of dimensionality. That is the dimension of the matching problem being higher than the total number of observations in a dataset. [Rosenbaum and Rubin \(1983\)](#) have shown that under unconfoundedness and overlap matching can also be done using a single variable such as the propensity score, $p(X) = Pr(D = 1|X)$, which captures the likelihood of receiving treatment given observed covariates. Using $p(X)$ rather than X , reduces the matching problem from a high dimensional problem to a single dimensional problem ([Heckman et al., 1997](#)). In this case, the treatment effect estimand of interest can be represented as:

$$ATT_{psm} = Exp_{p(X)|T=1}E[Y(1)|T = 1, P(X)] - E[Y(0)|T = 0, P(X)] \quad (2.5)$$

Where $Exp_{p(X)|T=1}$ is the distribution of the propensity scores, which acts as a weighting function. For ATT_{psm} to be a valid estimand of treatment effect, the two assumptions indicated above must hold. In practice, overlap in the conditional distribution can be verified using the propensity score. Unlike overlap, unconfoundedness cannot be directly tested. However, it might have testable implication such as checking that the propensity scores ensure covariate balance concerning the observed covariates.

From equation 2.5, it is evident that to be able to estimate the ATT I have first to estimate the propensity scores; this can be done using either a limited dependent variable model or using discriminant function analysis (DFA) ([Rosenbaum and Rubin, 1983](#)). Even though the two types of methods give identical results, the limited dependent variable model estimated through a logistic/probit regression is more

favoured. The problem with DFA is that it requires stringent assumptions of normality, which are usually violated in a multivariate setting where qualitative variables are among the explanatory variables (See [Press and Wilson, 1978](#), for details). For this reason, many prefer to use the logit or probit regression to predict the propensity scores as I do here.

A crucial step in estimating the p-score using the logit or probit model is the decision on which covariates to use ([Caliendo and Kopeinig, 2008](#)). As already discussed, one of the assumptions to be satisfied before using the PSM method is unconfoundedness, which requires the outcome variable to be independent of treatment conditional on the p-score. In this regard, [Smith and Todd \(2005\)](#) have pointed out that only variables influencing both the participation decision and the outcome variable should be included in the logistic regression. Additionally, no variable should be included if it is affected by treatment. Hence, one has to rely on either economic theory, previous research, or knowledge about the institutional settings to determine these variables ([Caliendo and Kopeinig, 2008](#)). For my case, the choice of variables is based on previous literature on household savings in developing countries (e.g. [Mikesell and Zinser, 1973](#); [Deaton, 1989](#)) and whether the variables affect the potential outcomes. The studies on saving in developing countries have shown that household saving depends mainly on household composition and wealth. But despite these two variables being found to be an important determinant of saving, they are not the only variables that explain variation in saving. [Browning and Lusardi \(1996\)](#) have highlighted that the variation in saving can also depend on age, household composition, income, education, and wealth. Accordingly, the variables I use for the propensity score model are: household size, gender of the household head, proportion of household members with primary education, indicator for ethnicity of the household head, household income, indicator for marital status of the household head, indicator for whether the household is a transfer recipient or not, characteristic of the household dwelling, proportion of household members in informal and farm employment, and whether the household lives in a district with a major financial institution such as a bank or microfinance institution. Evidence also indicates that these variables can affect potential outcomes such as household spending on consumption ([Hassan and Babu, 1991](#)); education ([Tilak, 2002](#)); food (See [Strauss, 1982](#),

on how income and household composition affect food expenditure); (See [Parker and Wong, 1997](#); [Rous and Hotchkiss, 2003](#), on how income and dwelling conditions can affect health expenditure); asset ownership (See [Yamokoski and Keister, 2006](#), on determinants of women asset ownership).

Therefore, the general specification of the propensity score model is given as follows:

$$P(T = 1|X) = F(\text{ageh}, \text{edulevel}, \text{hysize}, \text{female}, \text{totinc}, \text{dwell}, \text{farm}, \text{informal}, \text{transfer}, \text{ageh}^2, \text{edulevel}^2, \text{hysize}^2, \text{transfer} * \text{totinc}, \text{transfer} * \text{female}, \text{ethnic},) \quad (2.6)$$

To match on the $p(X)$, many different algorithms are available such as the nearest neighbour, calliper and radius, stratification and interval, kernel and local linear, and inverse probability weighting. Making a choice on which matching algorithm to use is still not clear-cut ([Huber et al., 2013](#)). Here I use the kernel method (details of this method can be found in [Heckman et al. \(1998\)](#)) for two reasons: Firstly, it is a non-parametric method; hence, does not impose any functional form restrictions. Secondly, unlike the first three methods, it uses data on the entire individuals in the control group to construct the counterfactual. For the kernel method, treated units are matched with control units based on weights that is inversely proportional to the distance between their propensity scores. Thus, control units whose propensity scores are closer to the treated units get more weight than those with distant propensity scores from the treated units. There are several kernel-based matching methods (See [Frölich, 2004](#)), but I used the kernel ridge regression (KRM) with bias adjustment method. According to [Huber et al. \(2013\)](#) KRM has superior finite sample properties than other kernel regression methods and [Abadie and Imbens \(2011\)](#) have shown that bias-adjusted matching estimators outperform simple matching or regression estimators. Even though I use the kernel algorithm, as recommended in the literature, I do a robustness check of the results against the use of alternative matching algorithms.

A major concern when using PSM to estimate treatment effect is the failure to account for all relevant covariates; particularly, covariates that cannot be observed.

Since the central assumption of matching methods is that selection is due to observed covariates and conditional on these covariates treatment is as good as random, failure to account for relevant covariates could bias treatment effects, and PSM is not robust against such "hidden bias" (Caliendo and Kopeinig, 2008). In this regard, it is a useful exercise to check the extent to which the impact estimates of a PSM are sensitive to the existence of unobserved confounders. A common way of doing this is the construction of the so-called Rosenbaum bounds, which is an idea introduced by Rosenbaum (2002). It involves the introduction of some hidden bias into the selection process and assessing how strong; such bias has to be to influence the unbiasedness of the matching estimate (Rosenbaum and Silber, 2009). Given that the approach is practically effortless to implement, I use it here to test the sensitivity of the PSM estimates to unobserved confounders.

DR Approach

The problem in using the propensity score to estimate the treatment effects is that the estimator is biased if the treatment assignment model (i.e. the p-score model) or even the outcome model is not correctly specified. Thus, when one is not sure if the treatment model is correctly specified, usually the case in a parametric specification of the model, then, it is desirable to use an estimator that is robust to such misspecification; hence, the rationale behind the popularity of the DR estimator. Such estimators remain consistent when either the model of the potential outcome or treatment assignment is misspecified (Bang and Robins, 2005). Therefore, the model is doubly robust because it requires either the outcome model or the treatment model to be correctly specified and not both (Wooldridge, 2010, p. 930). In this regard, the doubly robust estimator offers the researcher the opportunity to address the problem of model misspecification partially.

In applying the DR method, I follow the approach of Wooldridge (2007). Suppose a model of the potential outcome is, respectively, $E\{Y(1)|X\}$ and $E\{Y(0)|X\}$ for treated and untreated units, and $E(D = 1|X) = p(X)$ is a model of treatment mechanism. Wooldridge (2007) indicates that the estimand of treatment here can be

represented as:

$$ATT_{DR} = \left\{ E \left[\frac{DY(1)}{p(X)} | X, T = 1 \right] - E \left[\frac{(1-D)}{1-p(X)} Y(0) | X, T = 0 \right] \right\} \quad (2.7)$$

The ATT_{DR} can be estimated using a two-step approach [Wooldridge \(2010\)](#). In the first step, one estimates the treatment model to get the p-scores, and in the second step, a weighted regression is done to estimate the outcome model where the inverse p-scores are used as weights. [Wooldridge \(2007\)](#) provides the proofs that using such an approach produces a doubly robust estimator; (See [Wooldridge, 2010](#), for detail coverage). Therefore, I gauge the robustness of the propensity score estimates using the doubly robust estimator.

2.4 Data and Sample Characteristics

Gambia is one of the smallest and poorest countries in mainland Africa. With a population of about 2 million and a GDP per capita of \$473 (World Bank, 2016), it is certainly among the 20 poorest nations of the world. Like in many developing countries, poverty in Gambia continues to be a rural phenomenon; more than 70 per cent of the rural population falls below the international poverty line.

The data I used came from Gambia's third IHS that was conducted by Gambia Bureau of Statistics (from here GBoS) between May 2015 and April 2016. The IHS is among series of household surveys regularly (usually with a five to six years interval) performed by GBoS in collaboration with its international partners such as the World Bank, United Nations Development Program (UNDP) and United Nations Children's Fund (UNICEF). The carrying out of household surveys in Gambia started in 1989, but the first IHS was conducted in 2003/04 and the second in 2010 ([GBOS, 2017](#)). The primary purpose of the third IHS is to collect data on household poverty and vulnerability in Gambia to encourage evidence-based policy making and also to monitor the country's progress towards the attainment of her development goals ([GBOS, 2017](#)). As a result, richer data on households was collected in this survey round than any of the previous series. Also, the latest IHS also covered more households relative to last household surveys; for instance, the IHS 2003/04

and 2010 included only about 4800 households while this IHS involve over 13,000 households.

As a sampling frame, the survey used Gambia Population and Housing Census 2013; hence, all residential households in Gambia were eligible to participate in the survey. Gambia has 8 local government areas that are divided into 38 districts and two municipalities. In collecting census data, districts are divided into clusters of settlements referred to as enumeration areas (EAs) that are classified as either rural or urban. In sampling households for this survey, a multi-stage sampling design was implemented wherein EAs were used as primary sampling units. Hence, in the first sampling stage, 667 EAs were randomly selected, and in the second stage, 20 households from each EA are randomly chosen from a list of all households in the EA for interviews. A total number of 13,340 households were selected for the survey. However, due to nonresponses, only 13,281 households were successfully interviewed. The survey constituted four modules: (1) Household and individual level questionnaire that collected information on socio-economic indicators at both levels; (2) Consumption questionnaire that collected data on household consumption; (3) Price questionnaire that collected data on food prices; (4) Community questionnaire that collected data on community indicators. The latter was, however, administered to just a selected number of communities. In this study, I use data mainly from module 1, 2, and 3. However, the variables used in this study are primarily derived from module 1 and 2.

Among the indicators used, it is important to briefly describe how I derive the five outcome variables(i.e. total expenditure, education expenditure, food expenditure, health expenditure, and durable asset ownership) from the data. For the other variables, a brief description of each is provided in Table 2.1. Total expenditure is the sum of household spending on food and nonfood expenditure. Education expenditure constitutes household spending on education of members enrolled in schools in the last academic year prior to the survey; thus, in accordance with UNESCO guidelines, these include spending on items such as school fees; purchased of uniforms, textbooks, and examination fees; and payment for ancillary services such as fares to schools. Health expenditure captures household out-of-pocket spending on health-care. It includes items such as spending on consultations, dental fees, injections, lab

TABLE 2.1: Definition of Variables

Variable	Description
<i>Outcome variable</i>	
Total expenditure	Monthly total per capita expenditure (in GMD)
Education expenditure	Monthly education per capita expenditure (in GMD)
Food expenditure	Monthly food per capita expenditure (in GMD)
Health expenditure	Monthly health per capita expenditure (in GMD)
Durable asset	Number of durable assets own by a household
<i>Observed covariates</i>	
Household size	Total number of people in a household
Ethnicity	Ethnicity of the household head
Farm	Proportion of household members who are employed as a farmer
Self-employed	Proportion of household member who are self-employed
Married	Proportion of household members who are married
Marital status	Marital status of the household head (1=married, 0=otherwise)
Income	Total income of the household
School	Proportion of household members who have ever attended school
Education level	Proportion of household members with at least 8 years of formal education
Transfer	Households has received a transfer from a relative in the past 12 months (1=true, 0=otherwise)
Age	Age of the household head in number of years
Dwell noalign	Type of household dwelling (1= 1 with 1 HH ; 2= > 1 with > 1 HH; 3 = > 1 with 1 HH; 9 = Others)
District_bank	District has a formal financial institution provider

Definition of all variables that used in the analysis. Note: HH = Household

fees, scanning, X-ray, delivery, immunisation, drugs, and other charges. Durable assets ownership is the sum of durable assets owned by each household. The list of durable assets includes three main types of assets: home furniture, home appliances, and means of transport. Except for durable asset ownership, all the outcome variables are expressed in per capita terms using household size. However, monthly per capita food expenditure is shown in terms of adult equivalent units; this is so because adult equivalent scales are a more accurate reflection of divergence in food demand at the household level. The adult equivalent scales used were taken from the 1998 national poverty survey report by [Government of The Gambia \(1998\)](#).

Descriptions of all the variables and summary statistics are, respectively, reported in Table 2.1 and Table 2.2. Note that all the continuous variables reported in the table are winsorized at the 1st and 99th percentile; this was done to get rid of outlier observations. The mean monthly per capita total expenditure for all households

in the sample is about GMD 2063 (about \$43), and it is higher (20 per cent more) for households with access to saving than those without access to formal saving. For monthly per capita expenditure on food, it is also higher for treated households (i.e. those with access to formal saving) than untreated households (i.e. those without access to formal saving); in particular, the latter group spends on average about 41 per cent less on food. In the pooled sample, monthly per capita spending on food averages GMD 321 (about \$7) per month. Such low levels of monthly per capita food expenditure in the sample corroborate the high degree of poverty in Gambia. In fact, by the national food poverty line of about GMD 983 (about \$21), the estimations of the poverty rate indicate that about 42 per cent of households in the sample live in extreme poverty; in line with the national food poverty rate of about 48.6 per cent.

Regarding durable asset ownership, households in the treatment group hold almost twice more durable assets than those in the comparison group. The result for the pooled sample shows that on average households own more than five durable assets. It can also be seen that households that are treated tend, on average, to spend more on education than those not treated. The median annual per capita education expenditure (not reported) in the pooled sample is about GMD 402 (about \$ 8.4), which indicates that education spending is in general low; this is a stylized fact in developing countries. According to [Banerjee and Duflo \(2007\)](#), one possible explanation is that most poor households in these places send their kids to public schools and these do not ask for fees.

As shown in the last column of the table, all the differences in means for the outcome variables, except for monthly per capita total expenditure, are statistically different from zero. However, ascribing these differences to differences in formal saving ownership can be misleading at this point; as will be discussed shortly (but as seen in the Table 2.2) observed characteristics are also markedly different between the two groups. So, unless I account for these differences, I cannot attribute the differences in outcome between the two groups to participate in formal saving interventions.

For the observed covariates, Table 2.2 reports that untreated households are bigger in size than treated households; the average household size in the pooled sample is 8 members. Education level is also different in the two groups; the number of

TABLE 2.2: Descriptive Statistics

	Comparison	Treatment	Pooled	Difference
	Mean & sd	Mean & sd	Mean & sd	mean & sd
Total expenditure	2014.3 (44283.2)	2426.0 (2406.2)	2062.5 (41617.0)	-411.7 (1126.1)
Education expenditure	609.8 (1166.7)	1320.2 (2213.2)	702.5 (1370.8)	-710.4*** (44.7)
Food expenditure	306.6 (235.9)	431.2 (376.8)	321.2 (259.6)	-124.6*** (6.9)
Health expenditure	7.4 (41.38)	14.3 (99.94)	8.2 (51.88)	-6.9*** (1.396)
Durable asset	5.0 (2.870)	8.2 (3.790)	5.4 (3.164)	-3.2*** (0.081)
Household size	8.027 (5.272)	7.512 (5.660)	7.966 (5.322)	0.514*** (0.143)
Ethnicity	2.523 (1.920)	2.592 (1.987)	2.534 (1.931)	-0.068 (0.108)
Farm	0.187 (0.269)	0.128 (0.237)	0.180 (0.266)	0.059*** (0.007)
Self-employed	0.0133 (0.0682)	0.0157 (0.0752)	0.0136 (0.0690)	-0.0020 (0.002)
Married (proportion)	0.371 (0.205)	0.393 (0.252)	0.373 (0.212)	-0.022*** (0.006)
Marital status (household head)	2.258 (1.165)	2.086 (0.991)	2.232 (1.143)	0.171** (0.061)
Household total income	1034.1 (2930.6)	2246.4 (4630.5)	1176.0 (3200.5)	-1212.3*** (86.0)
School	0.376 (0.484)	0.644 (0.479)	0.407 (0.491)	-0.268*** (0.013)
Education level	5.453 (4.652)	3.594 (4.070)	5.234 (4.626)	1.859*** (0.124)
Transfer	0.376 (0.484)	0.442 (0.497)	0.384 (0.486)	-0.066*** (0.013)
Age	44.53 (14.81)	41.89 (13.24)	44.14 (14.62)	2.64*** (0.78)
N	11,717	1,564	13281	

Descriptive statistics of outcome and observed characteristics. Reported under the columns are the means and standard deviation of the variables for household with access to formal saving accounts (treatment) and households without access to formal saving accounts (comparison) and all households (pooled). Test statistics from the test of mean difference between the two groups is reported in the last column. Note: reported in parenthesis are the standard deviations; all continuous variables were winsorized at the 99th percent level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

household members that have completed primary education is lower for households in the treated sample than the comparison sample. This is a bit surprising given that the latter group spends less on education per person than the former. However,

TABLE 2.3: Poverty and Inequality Indicators

Indicator	Comparison	Treatment	Population
Poverty rate	0.528	0.290	0.478
SST index	0.418	0.235	0.385
Gini index	0.458	0.381	0.448

Level of poverty and inequality in the two groups. Note: household weights were used; SST = Sen, Shorrocks and Thon measure of poverty which is the weighted sum of the poverty gap. All measures are based on an absolute poverty line of 1503 Gambian Dalasis.

given that primary and secondary education in Gambia (for public schools) is free, one possible explanation could be that households in the treated group have more members in higher education, where fees can be quite expensive. For households in both the treated and non-treated sample, many are employed in the agricultural sector as farmers; the average proportion of household members in farm-related employment is 18 per cent in the pooled sample. Although more households in the treated sample are formally employed (i.e. in wage employment or self-employed), in general, very few household members in the sample are formally employed.

Given that transfers from family members can be an essential driver of household saving, an indicator variable for transfer received is also reported. The proportion of households who said to have received a transfer is less in the comparison sample than in the treatment sample. The average percentage of households in both samples who reported to have received a transfer is more than 30 per cent.

Regarding orthogonality of the observed covariates in the two groups, the last column of the Table 2.2 shows that except for three indicators (monthly per capita total expenditure, ethnicity of the head, the proportion of self-employed household members) all the observed covariates are highly significantly different in the two groups. Hence, any determination of causal impact that involves comparing these groups and where the average outcome of the untreated group serves as a proxy for the counterfactual outcome of the treated group must account for differences in observed characteristic, as this might be an indication of selection bias. The methods I used to address this issue are described in the previous section.

In the discussions above, I briefly stated that the low food monthly per capita

expenditure could be due to the widespread nature of poverty in Gambia and by extension in the two groups. Thus, here I provide more detail information on the kind of poverty and inequality in the two groups. In this regards, in Table 2.3 I report three indicators that capture poverty and inequality: poverty headcount index, Gini index, and Sen, Shorrocks and Thon (SST) poverty index. These indicators were computed using the data on household consumption. Accordingly, as poverty line, I used the national absolute poverty line developed by GBoS from the IHS 2015/16 data. GBoS constructed the national poverty line using the commonly used cost of basic needs approach, which measures poverty based on a households' ability to afford the cost of basic needs such as daily calorie needs plus clothing and shelter (See [Ravallion, 1998](#), for details). Based on this approach household absolute poverty line in Gambia is set at 1503 Gambia dalasis (GMD) per month. Therefore, using this poverty line Table 2.3 shows that the poverty rate is higher for households without access to formal saving accounts than it is for households with access to such accounts. The Gini index, which measures inequality, is also higher for the comparison group (i.e. households with a formal saving product); hence, inequality is lower for the latter group. The SST index, which captures the intensity of poverty by combining the first two measures plus the poverty gap, shows that poverty is more intensive for households without ownership of regular accounts. A measure of the poverty depth using the poverty gap, shown in Figure 2.1, indicate that poverty depth is higher for households without formal financial resources than it is for households with such resources. Therefore, even though poverty and inequality are pervasive in both groups they are higher for households who do not own a saving account; this could be an indication that poverty might be a reason for low ownership of regular accounts by most households in Gambia. This result is in line with the evidence globally that many adults do not own accounts because of lack of a stable income source ([Demirgüç-Kunt et al., 2017](#)). Note that since I have not controlled for differences in covariates, I am talking in terms of correlations only.

FIGURE 2.1: Depth of Poverty

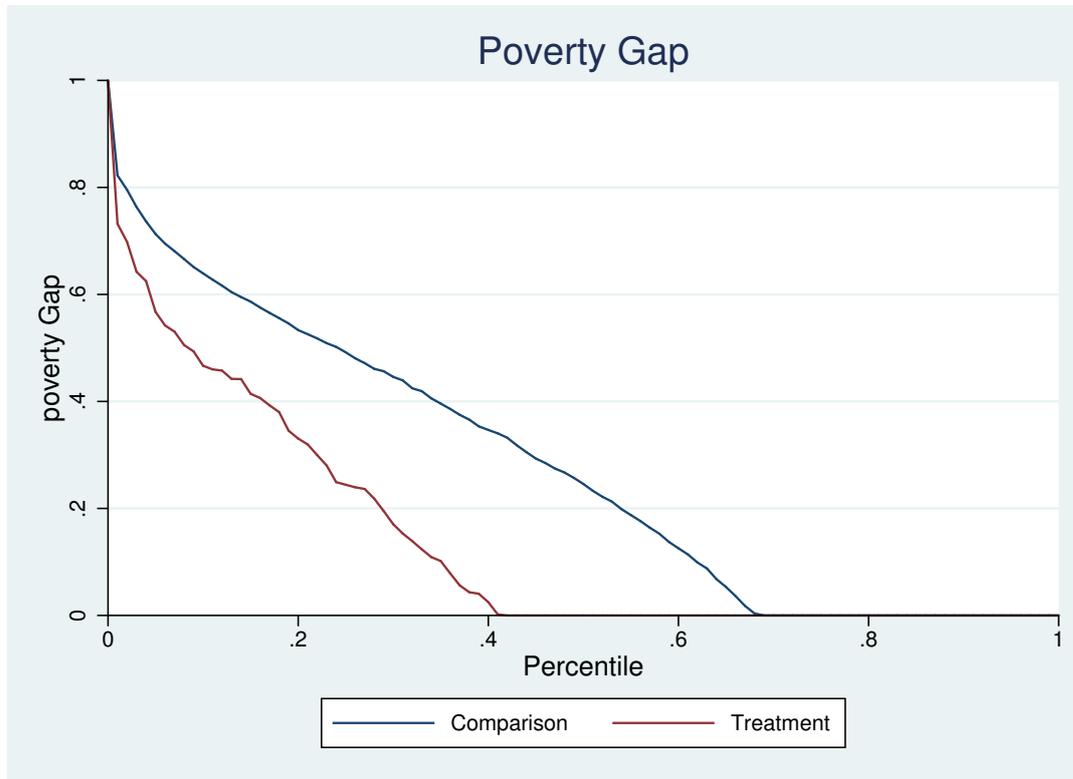


Figure shows the depth of poverty in the treatment and comparison and treatment group. The poverty depth is measured using the poverty gap, which gives the ratio by which the mean income of the poor is below the poverty line. The poverty line is set at the national absolute poverty line of GMD 1503.

2.5 Empirical Results and Discussion

The results from the treatment effect estimations - for both the propensity score model and the doubly robust model - are reported in Table 2.7 under ATT_{PSM} and ATT_{DR} respectively. However, before the treatment effects are estimated, one has first to specify and estimate a propensity score model. To this effect, I used a logistic model for predicting the likelihood of a household to own a formal saving account given the household's observed characteristics mentioned in 2.3.1. The outcome of the estimation is reported in Table 2.4. The likelihood ratio chi-square test statistics of 357.93 with a p-value of 0.000, not reported in the table, indicate that the observed covariates I used does well in predicting the probability of owning a saving account. Moreover, all the covariates except education level have the expected effect on the probability of owning a regular saving account; as expected household size, income,

TABLE 2.4: Propensity Score for Savings Ownership

	Coefficient	Std. Error	Z-Statistic
HHsize	0.394***	0.0831	4.74
HHsize*HHsize	-0.009	0.0048	-1.93
Age	0.035	0.0279	1.26
Age*Age	-0.000	0.0003	-1.20
Ethnicity	-0.033	0.0360	-0.92
Transfer*Female	-0.082	0.3389	-0.24
Edulevel	-0.695***	0.0761	-9.14
Dwell	0.069	0.0668	1.04
Female	-0.594	0.3349	-1.77
Female*Ethnicity	0.061	0.0756	0.81
Transfer	-0.203	0.2144	-0.94
Edulevel*Edulevel	0.026***	0.0055	4.63
District_Bank	0.210	0.1348	1.56
LogIncome	0.289**	0.1108	2.61
Farm	-0.202	0.2468	-0.82
Informal	-0.187	0.5376	-0.35
Income	0.000	0.0000	0.73
Transfer*Income	0.000*	0.0000	2.06
Constant	-4.866***	0.9632	-5.05
Pseudo R2	0.174		

Estimation result of the propensity score model. Note: Std. error = Standard errors of the coefficients; Z-Statistic = Statistics from the standard normal distribution; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

living in district with a formal bank all have a positive effect on the predicted probability of owning regular saving account.

Despite briefly describing the estimates from the logistic model, these estimates are in themselves not very important (Lee, 2013). So what is useful is the extent to which they help in the achievement of covariate balance. Checking for covariate balance is therefore very crucial in such applications. This can be done both before matching and after matching, and several approaches have been suggested (See Lee, 2013, for details). I used the standard differences test and variance ratio approach that was first suggested in Rosenbaum and Rubin (1985) and commonly used in the literature. The results of the balance checks are reported, respectively, for PSM and DR in Table 2.5 and 2.6. Regarding the standard difference, the recommendation (See Rosenbaum and Rubin, 1985, for details) is that it should not be more than 20% (in absolute terms) as anything above this is considered a large difference that signals covariate imbalance. Ideally, however, a standard difference of less 10% is usually preferred. For the variance ratio, it is recommended that its values should lie between 0.5 and 2. Given these recommended values, the balance test results in table

TABLE 2.5: Balancing Results (PSM-Kernel Ridge Regression)

Standard Differences & Variance Ratios

Variable	Standard Diff.		Variance Ratios	
	Raw	Matched	Raw	Matched
Age	-0.215	0.005	0.827	0.990
Hhsize	-0.330	0.033	0.913	0.967
Edulevel	-0.680	0.011	0.635	1.104
Female	-0.160	0.015	0.776	1.028
Totinc	0.791	0.048	2.071	1.002
Dwell	0.074	0.047	1.621	1.280
Farm	-0.263	-0.001	0.758	1.078
Informal	0.037	0.029	1.394	0.946
Transfer	0.003	0.034	1.003	1.017
Age _{sq}	-0.215	0.005	0.827	0.990
Hhsize*hhsize	-0.227	-0.023	0.992	1.046
Edulevel*edulevel	-0.378	.020	0.897	1.238
Transfer*totinc	0.437	0.067	3.493	1.231
Transfer*female	-0.129	0.001	0.739	1.002
2.Ethnicity	-0.371	0.0253	0.678	1.043
3.Ethnicity	0.071	-0.009	1.173	0.981
4.Ethnicity	0.065	-0.020	1.218	0.953
5.Ethnicity	-0.012	-0.008	0.952	0.967
6.Ethnicity	0.075	0.019	1.423	1.075
7.Ethnicity	0.097	0.005	3.050	1.083
8.Ethnicity	0.128	0.066	2.722	1.612
9.Ethnicity	-0.042	0.034	0.696	1.505
10.Ethnicity	-0.060	-0.020	0.506	0.762

Results from the balancing test of observed covariates from the kernel ridge regression model. Notes: Raw = unmatched sample and Matched = matched sample; Age_{sq} = Age square; $Hhsize$ = Household size; $Totinc$ = Total income; $Edulevel$ = Education Level; Standard Diff. = standardized difference. The standardized difference and the variance ratios are based on Rosenbaum and Rubin (1985). Ideally, the standardized difference of covariates between the two groups shouldn't be above 20% (absolute value) and variance ratio between 0.5 and 2 is desired. The two statistics are reported for the unmatched and matched sample.

2.5 and 2.6 show that the propensity scores (in both the matching model and the robust double model) does well in balancing the covariates among the two groups. Specifically, before matching only a few indicators (proportion of household in informal employment, the dwelling type of the household, and whether the household is a transfer recipient) have a standardise difference below 10%; in fact, most of them are above 20%. However, after matching, all the covariates have now a standard-ised mean difference of less than 10%. A similar observation can be made from the variance ratio estimates. In particular, even for the covariates with variance ratios

FIGURE 2.2: Cumulative Plot of Propensity Scores

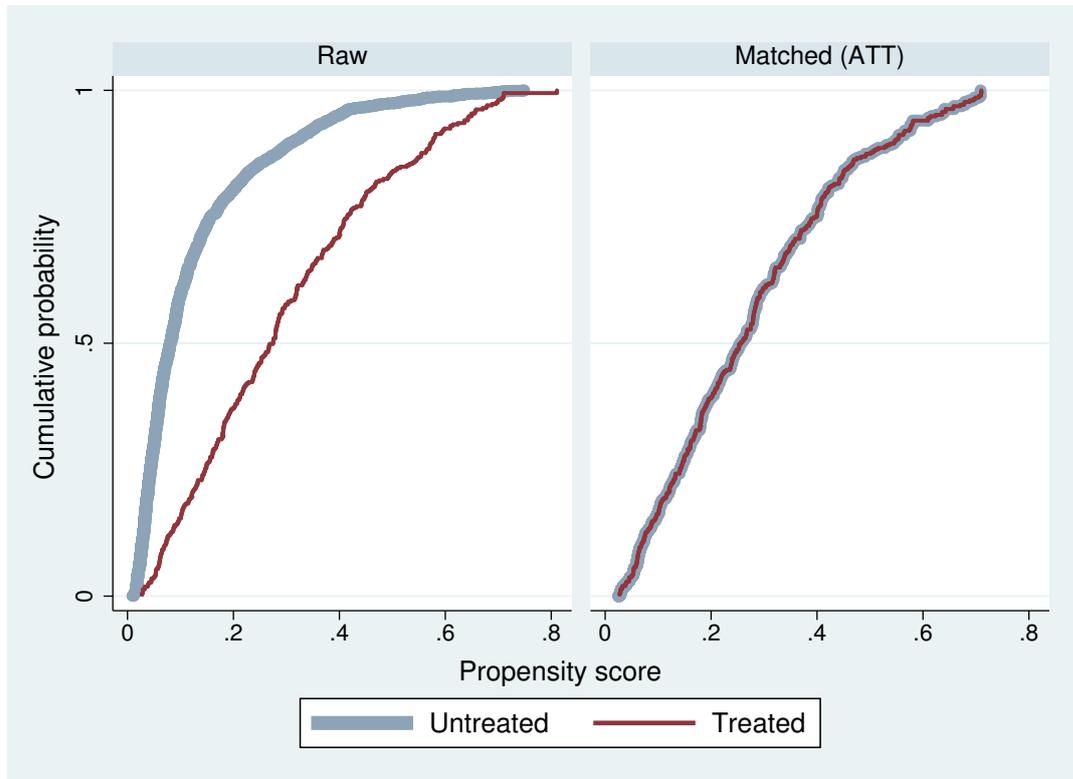


Figure shows cumulative probability plots of the p-scores before matching (Raw) and after matching (Matched). Note: ATT = Average Treatment Effects. The vertical axis reports the probability that the p-score is less than or equal to a given p-score.

outside the 0.5-2 range, their variance ratios fall within the recommended range after matching. Therefore, taking together the results here indicate that the propensity scores produce a satisfactory balance. This can also clearly be seen in the cumulative plots in Figure 2.2; the distribution of the propensity scores get similar after matching than before matching.

After getting a satisfactory balance, next, I check for the degree of overlap of propensity scores in the two groups. This is shown in Figure 2.3. Despite the degree of overlap being stronger at lower propensity scores than higher propensity scores, overall the figure shows that the overlap in propensity scores between the two groups is fairly good; i.e. for all the propensity scores, there are households in both the comparison and treatment group. This ensures that for every household that owns a formal saving account I can find a household without a formal saving account that it can be compared to via similarity in observable characteristics. Given

TABLE 2.6: Balancing Results (DR)
Standard Difference & Variance Ratios

Variable	Standard Diffs		Variance ratios	
	Raw	Weighted	Raw	Weighted
Age	-0.215	0.011	0.827	0.922
HHsize	-0.330	-0.005	0.913	0.981
Edulevel	-0.680	0.009	0.635	0.971
Female	-0.160	0.023	0.776	1.044
Farm	-0.263	0.031	0.758	1.132
Informal	0.037	0.023	1.394	1.065
Transfer	0.003	-0.059	1.003	0.979
Totinc	0.792	-0.049	2.071	0.901
Age _{sq}	-0.215	0.008	0.827	0.989
Dwell	0.074	-0.029	1.620	0.763
Hhsize*hhsz	-0.227	-0.005	0.818	0.933
Edulevel*edulevel	-0.378	0.014	0.489	0.721
Transfer*totinc	0.438	0.031	3.493	0.996
Transfer*female	-0.130	0.016	0.739	1.040
2.Ethnicity	-0.371	.0253	0.678	1.043
3.Ethnicity	0.071	-0.009	1.173	0.981
4.Ethnicity	0.065	-0.020	1.218	0.953
5.Ethnicity	-0.012	-0.008	0.952	0.967
6.Ethnicity	0.075	0.019	1.423	1.075
7.Ethnicity	0.097	0.005	3.050	1.083
8.Ethnicity	0.128	0.066	2.722	1.612
9.Ethnicity	-0.042	0.034	0.696	1.505
10.Ethnicity	-0.060	-0.020	0.506	0.762

Results from the balancing test of observed covariates from the doubly robust model estimated using the inverse probability weighting regression adjustment estimator. Notes: Raw = unmatched sample and Matched = matched sample; Age_{sq} = Age square; $HHsize$ = Household size; $Totinc$ = Total income; $Edulevel$ = Education Level; Standard Diff. = standardized difference. The standardized difference and the variance ratios are based on Rosenbaum and Rubin (1985). Ideally, the standardized difference of covariates between the two groups shouldn't be above 20% (absolute value) and variance ratio between 0.5 and 2 is desired. The two statistics are reported for the unmatched and matched sample.

that the overlap graph was done in the region of common support, the figure shows that the distribution of the propensity scores in the region of common support appears good enough; this is necessary to avoid the problem of using poor matches when estimating the treatment effects. So next I discuss the treatment effect estimation results.

As mentioned in section 2.3.1, I used kernel ridge regression algorithm with

FIGURE 2.3: Overlap Graph of the Propensity Scores in Matched Sample

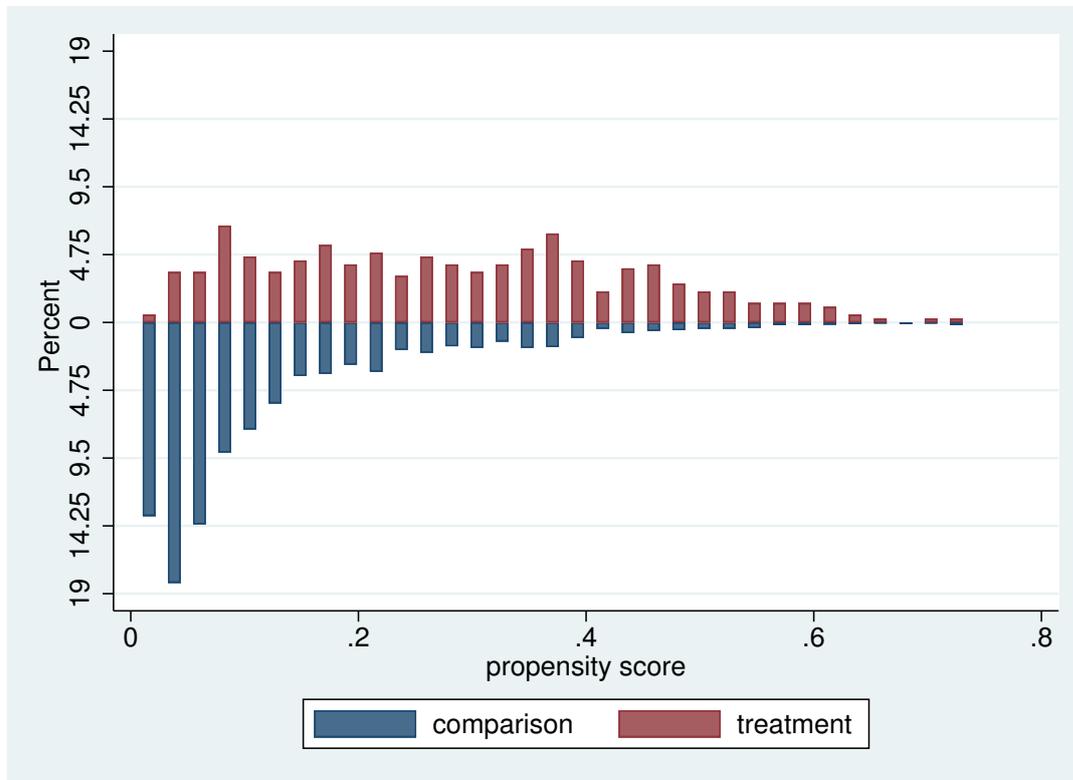


Figure is a Barchart plot of the p-scores for the comparison and treatment group. The height of a bar gives the percentage of households with p-scores equivalent to p-score of that bar.

biased-adjustment to estimate the treatment effects via PSM. Like any kernel based-method, two crucial choices have to be made: a choice of what type of kernel to use and a decision regarding the smoothing term - i.e. bandwidth. I used the Epanechnikov kernel and allowed the bandwidth to be determined via the pair-matching approach of [Huber et al. \(2013\)](#). In a ridge regression, one has also to set the ridge term. As recommended by [Huber et al. \(2013\)](#), I set this term at 0.3125. Furthermore, I used bootstrapping to estimate the standard errors and set the number of replications at 1000; additionally, standard errors were clustered at the EA level. The estimations were done in STATA using the KMATCH command of [Jann \(2017\)](#). The results from this exercise are reported in row 2 of Table 2.7. The second row of the table contains the results from the DR estimation algorithm. All the impact estimates are in terms of average treatment effect on the treated (ATT).

In Table 2.7, the PSM estimates show that ownership of a formal saving account

TABLE 2.7: Treatment Effects

	Total Expenditure	Education	Food	Health	Durable Assets
ATT_{PSM}	513.03*** (95.885)	443.05*** (124.744)	75.93*** (24.231)	1.91 (1.656)	1.13*** (0.298)
ATT_{DR}	501.10*** (92.798)	369.42*** (120.945)	70.02*** (22.141)	1.00 (1.482)	1.06*** (0.297)
comparison group					
Mean	2014.3	609.8	306.6	7.4	5.0
Std. Dev	44283.2	1166.7	235.9	41.38	2.870

Estimation results on the Average Treatment effect on the Treated (ATT) from the Propensity Score Model (PSM) and Doubly Robust (DR) Model. Notes: ATT_{PSM} = estimates of ATT from the PSM model; ATT_{DR} = estimates of ATT from the DR model; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported in parenthesis are: For ATT_{PSM} , the bootstrap standard errors with 1000 replications and clustered at the EA level; For ATT_{DR} , the cluster (clustering at the EA level) robust standard errors. We use clustering to adjust for the fact that the data was collected using cluster random sampling where clustering occurred at the EA level. The ridge term for the kernel matching is set at 0.3125 and bandwidth is determined via pair-matching.

has a positive and significant impact on household monthly per capita total expenditure. In particular, households that have access to a saving spend about 513 dalasis¹ more than those that do not have access to a formal saving account. Thus, formal saving increases monthly per capita total household spending by about 25%. In terms of standard deviations, the effect is just 0.012, which is very small; this is due to the high variability of total expenditure on households in the comparison group. It was due to this reason that all continuous variables were winsorized at the 1st and 99th percentile level before using them in the treatment effect estimation. An estimate of the impact of 501 for total expenditure in row 2, which is also statistically significant, indicates that the doubly robust estimate is indeed similar to the kernel estimate.

Regarding annual per capita household education expenditure, the PSM estimate in Table 2.7 shows that access to formal means of saving by households increases monthly per capita household expenditure by about 73% - about 0.38 standard deviation, which seems significant. However, in terms of Cohen's d (See [Cohen, 1992](#)) can be considered a medium size effect, which is the highest impact of

¹The dalasis to dollar rate was about 47 at the time of writing

saving I find for the outcomes studied. The reason why formal saving account ownership leads to such a high impact on education than the other household indicators is not clear-cut. But I think this could be explained by the fact that households hold savings accounts mainly to set funds aside for footing education bills. However, I do not have enough information in the data to test for this; hence, this explanation remains a loose one. A similar causal impact estimate on education is obtained when the DR procedure is employed; the magnitude of the impact estimates are quite the same in the two approaches and both I get highly statistical significant impact estimate for per capita education spending. This is an indication that the impact estimate for education spending is robust across different specifications of the ATT. The PSM estimates also show that the causal impact of access to formal saving on the household monthly per capita food expenditure is positive and statistically significant. In particular, access to formal means of saving by a household increases the household monthly per capita spending on food by about 0.32 standard deviations. Again the DR estimate of the same impact is, in magnitude, very close to the PSM estimate and is statistically significant, which indicates that the effect I find is robust against alternative estimation methods.

For health expenditure, the causal impact is positive implying that access to saving increases household monthly per capita health expenditure. However, unlike the other outcomes already discussed it is both economically and statistically insignificant. The low economic size of the estimate can be attributed to the fact that self-reported household spending on health services in the dataset is generally low; the percentage share of household health expenditure in total household consumption is about 1%. In low-income countries like Gambia, many households access health care through public health facilities and the fees charged in these places are very minimal. As a result, direct out-of-pocket expenditures on health services are very low. In this regard, Gambia does not seem to face the problem of catastrophic health expenditure that characterises health care access in some developing countries ([World Health Organization and Others, 2005](#)). However, the low levels of private health financing plus little public funding (about just 11% of GDP) culminate to the low level of health care delivery in the country; health care services in Gambia is mostly (about 70%) financed via donor assistance ([Government of The Gambia,](#)

TABLE 2.8: Treatment Effects: Other Matching Algorithms

	Total Expenditure	Education	Food	Health	Durable Assets
$ATT_{NNM(1)}$	435.27*** (133.311)	377.76*** (170.640)	77.62*** (30.847)	1.50 (2.162)	1.180*** (0.347)
$ATT_{NNM(4)}$	536.41*** (104.576)	391.59*** (144.398)	69.35*** (25.793)	0.12 (1.780)	1.09*** (0.3305)
ATT_{Radius}	546.60*** (103.388)	393.67*** (137.808)	67.88*** (24.754)	0.20 1.842	1.09*** 0.299

Estimation results on Average Treatment effect on the Treated (ATT) for the outcome variables in the columns estimated using other matching algorithms: Nearest Neighbor Matching using a single neighbor ($ATT_{NNM(1)}$); Nearest Neighbor Matching using 4 neighbors ($ATT_{NNM(4)}$); Caliper or Radius matching (ATT_{Radius}). Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Reported in parenthesis are the bootstrap standard errors with 1000 replications and clustered at the EA level; For the radius matching, we set the caliper at 0.019.

2007).

Lastly, the results in Table 2.7 indicate that the causal impact of access to formal saving on household ownership of durable assets is positive and statistically significant. Specifically, the PSM estimate shows that household ownership of formal saving account causes about 21% increase in the number of durable assets ownership. Also, the estimation of the treatment effect using the DR gives about the same effect size of the impact (i.e. about 0.39 standard deviation) as the PSM; hence, similarly the treatment effect for durable assets ownership is robust to alternative treatment effect estimation methods.

For further robustness check, I also estimated the treatment effects using other matching algorithms such as nearest neighbour matching and calliper matching. The results from this exercise are summarised in Table 2.8. For the nearest neighbour matching, I made a distinction between using a single nearest neighbour in the treatment effect estimation and using four nearest neighbours in the treatment effect estimation. When carrying out the radius matching, I follow the approach of [Rosenbaum and Rubin \(1985\)](#) to set the calliper at 0.019. The estimates produced using these alternative algorithms of carrying out the PSM are generally quite similar to those obtained when the kernel method is used; just the magnitude of some of the impacts (e.g. total expenditure in NN(1)) are a bit different from the kernel estimates. Importantly, however, the statistical significance of all the impacts remain

TABLE 2.9: Sensitivity Analysis

Rosenbaum Bounds

Outcome variable	Significance level	$\Gamma = 1.0$	$\Gamma = 1.1$	$\Gamma = 1.2$	$\Gamma = 1.3$	$\Gamma = 1.4$	$\Gamma = 1.5$
Total expenditure	p^+	0.0000	0.0000	0.0000	0.0001	0.0005	0.0029
	p^-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Education	p^+	0.0268	0.0737	0.1559	0.2706	0.4046	0.5408
	p^-	0.0268	0.0078	0.0020	0.0005	0.0001	0.0000
Food	p^+	0.0013	0.0125	0.0611	0.1822	0.3755	.5916
	p^-	0.0013	0.0000	0.0000	0.0000	0.0000	0.0000
Asset ownership	p^+	0.0000	0.0000	0.0004	0.0032	0.0158	0.0537
	p^-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Sensitivity analysis to test for the effects of unobserved covariates using Rosenbaum Bounds. The significance level is the upper ($p^+ =$) and lower ($p^- =$) bound p-values for each level of Γ , which measures the odd ratio of owning a formal saving account for units with the same values of the observed covariates under hidden bias; it starts from 1.0 (%0 of hidden bias) to 1.5 (50% of hidden bias). Note: Health expenditure is omitted from table because it was found to be statistically insignificantly impacted by savings ownership.

unchanged regardless of the matching algorithm used. In light of this, I argue that the estimates I find here are robust both to alternative estimators and to different matching algorithms.

The output from the sensitivity analysis using the [Rosenbaum \(2002\)](#) approach are reported in Table 2.9. The Rosenbaum bounds were computed using a gamma (odd ratio of owning a saving account for units with the same values of the observed covariates) that ranges from 1 (no heterogeneity or hidden bias, i.e. treated and comparison units have the same likelihood of owning a saving account given their observed covariates) to a maximum of 2 (i.e. units with the same value of observed covariates could have up to 200% difference in their likelihood of owning an account due to unobserved confounders or hidden bias with a 0.1 increase). For each value of gamma, two levels of significance (p-values) are reported that are based on McNemar test: an upper bound and a lower bound level of significance. The p-values are reported in column 2 of Table 2.9. Given that for some of the outcomes the upper bound level of significance gets higher than the standard level of 5% at gamma higher than 1.5, reported in Table 2.9 are the results obtained for gamma 1 - 1.5.

The results show that the impact estimate of total expenditure remain statistically significant even if hidden bias introduces a heterogeneity of about 50% in the odd ratio of owning a formal saving account for units with the same values of the

observed covariates used for the matching. This implies that a mild hidden bias is not sufficient to undermine the results obtained. However, for the impact estimate on annual per capita education spending, it is sensitive to the mild difference in unobserved covariates in that even with a gamma of 1.1 the upper bound p-value is higher than the conventional level of 5%; hence, becoming insignificant at this level. The estimate of per capita food spending, on the other hand, is slightly less sensitive to hidden bias than per capita education spending as its upper bound of significance remain significant at a gamma of 1.1. However, it also becomes insignificant at 5% when gamma increases to 1.2 even though it is still significant at 10%. For asset ownership the results show that heterogeneity has to be about 60% high for the effects I find for this indicator to be statistically insignificant at the 10% level; at the convention significance level, even 40% of heterogeneity or hidden bias does not affect the significance of its impact estimates. Hence, broadly speaking the two impact estimates that appear to be robust to relaxing the assumption that all relevant unobserved covariates are also balanced are per capita expenditure and asset ownership. Having said that it is important to note that the sensitivity analysis results indicate just what happened in the worse case scenario. Therefore, the results they provide should be interpreted with care.

2.6 Conclusion

In this study, I provide evidence on the impact of ownership of formal saving accounts on household welfare in Gambia using a recently collected representative household survey and causal inference methods for observational studies. These rigorous techniques allow me to get a consistent estimate of the causal impact of access to formal financial products like savings on households wellbeing. I find evidence that in Gambia access to formal means of savings by households causes an increase in household well-being. In particular, using propensity score matching with kernel ridge regression, I find that household ownership of a formal saving product leads to an increase in total household spending by about 25%. It also increases the annual education spending of a household by about 73% as well as food

expenditure spending by about 25%, and household ownership of durable assets by 21%.

To check if the estimates from the propensity score model are robust to alternative specification of the treatment effects, I also estimated the treatment effects using a doubly robust method. Generally, the results from the doubly robust model are similar to those of the propensity score model - both in terms of magnitude and statistical significant. Hence, I conclude that the estimates I find using the propensity score model with kernel estimation method are robust to alternative specifications of the treatment effect model. Furthermore, I also checked whether estimates from the propensity score model are robust to alternative matching algorithms and I find evidence that the estimates remain somewhat the same irrespective of the matching algorithm used. Lastly, I also checked if the ratings are sensitive to the problem of hidden bias and I obtained that while the impact estimate of food expenditure and asset ownership are not sensitive to mild hidden bias the impact estimate of education and food expenditure is susceptible to such bias. In this regard, I postulate that the impact of saving on total spending and asset ownership provides the most robust evidence on the effect of saving on household welfare in Gambia.

Therefore, in total, the results I find here indicate that having access to formal accounts can have positive consequences on socio-economic outcomes of households in Gambia. From a broader perspective, therefore, I support the mounting evidence from experimental and non-experimental studies that savings promotion can be an excellent tool to promote socio-economic development in developing countries. For Gambia in particular, I provide rigorous evidence that ownership of formal savings accounts enhances household welfare. Thus, savings promotions could be an ideal tool to promote socio-economic development in the country via financial inclusion as the latter encourage households to make long-term investments that improve welfare. Hence, the government should intensify its efforts in promoting broader financial inclusion via access to more formal means of savings.

The main limitation of the study is that I do not have enough information from the data to analyse which specific aspects of the saving account ownership motivates the impact on socioeconomic outcomes revealed by the study. In the case of Gambia, this is quite important as it will indicate which aspects of savings can be promoted

for there to be positive impacts on household well-being. Thus, this aspect is something I leave for future research.

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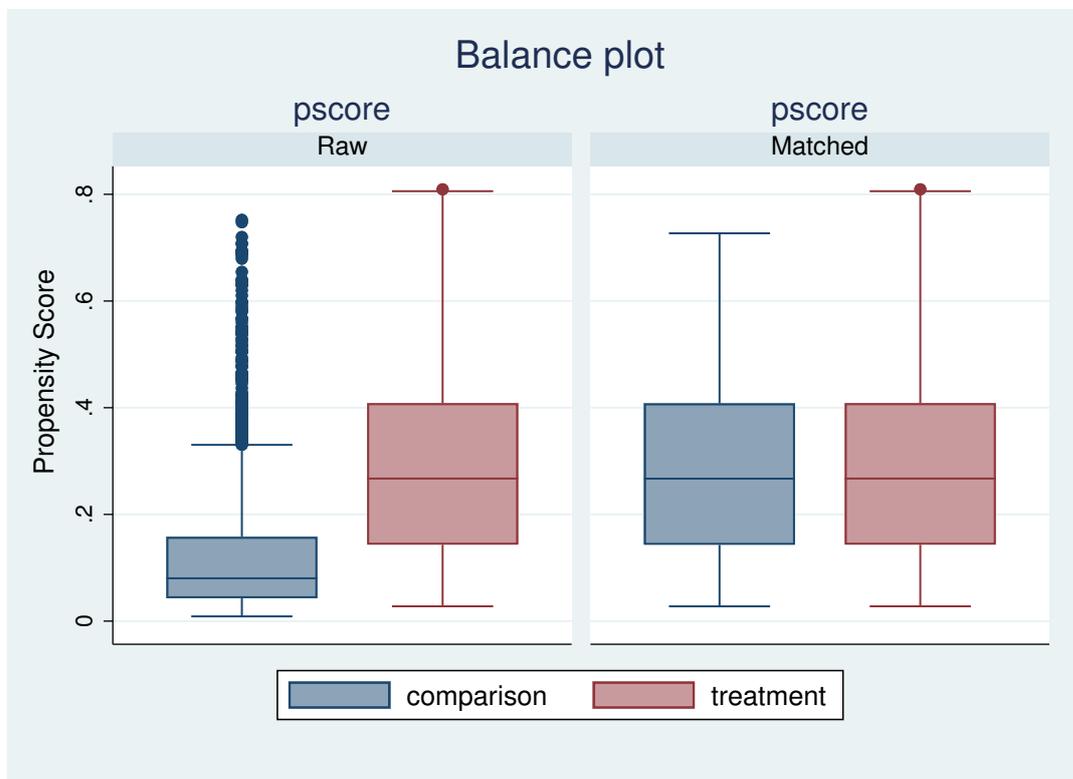
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Appendices

Appendix B

Additional Tables and Figures

FIGURE B.1: Boxplot of Covariate Balance



Graph shows covariate balance in the two groups using a box-plots. Box-plots are similar after matching than before matching.

Chapter 3

The Big Five Personality Traits and Borrowers behaviour: Evidence from Group-Based Lending in Gambia

3.1 Introduction

Among the various tools that have been advanced for dealing with poverty by economists, one that has received significant attention over the years, especially in developing countries, is the issue of financial inclusion; in particular, the access of credit services by the poor. Access to credit is necessary because the majority of the extreme poor in developing countries are dwellers of rural communities. In these places, there exist very few traditional money lending institutions. The absence of formal means of credit in areas that are predominantly inhabited by the poor is due to many factors, among them the fact that poor borrowers lack sufficient collateral to support their loan applications. Meanwhile, without access to credit low-income households cannot have access to capital required to finance projects that can get them out of poverty. It is for this reason that the provision of credit to the poor via non-conventional means (such as microcredit) is a valuable tool to boost global efforts to combat poverty and underdevelopment (See for instance [Khandker et al., 1998](#), on the welfare impacts of microcredit in Bangladesh). Such a notion to microcredit became popular following the successes of Mohammed Yunus and the

Grameen Bank in Bangladesh.^{1 2}

The central idea of microcredit (often also known as micro-lending) is the provision of credit, in the form of small loans, to low-income earners (mostly the extreme poor in rural areas in developing countries) some of whom have promising projects but lack credit access. By the way, the reason why access to credit in many low-income countries is low is that many of the formal credit providers in these places find lending to the poor unattractive as many of them are involved with highly risky activities, thus, with highly variable earnings. Hence, to ensure loans get to those that can repay, formal lenders impose a lot of stringent conditions that the poor usually find difficult to satisfy. Consequently, traditional means of credit creation emerge as a means to fill this void. However, these means of credit creation in rural areas come with very high interest rates, which makes it difficult for the poor to borrow and make ends meet. It is against this backdrop that various forms of micro-lending are viewed as an essential tool for dealing with the problem of credit access by the poor.

Among the different variants of micro-credit, one that has attracted much attention over the years is a group and joint liability lending. It has captured the attention of economists as one of the most promising means to get credit to those without access to formal credit (Wydick, 1999). In such schemes, a group gets a loan and all members of the group are responsible for its repayment; that is all individuals in a group are jointly liable for a loan. Such a lending program is ideal because it solves a fundamental problem in credit markets – the bottleneck of distinguishing between high-risk and low-risk borrowers due to information asymmetries. Besides, it also minimises the fixed cost associated with small loans (Karlan, 2005). The difficulty in screening poor borrowers plus lack of collateral and credit history increases the cost of lending to the poor (Aghion and Gollier, 2000). Group lending can reduce such cost by transferring the cost of screening and monitoring to borrowers themselves (Karlan, 2005); usually, borrowers have more information about each other

¹As of 2011 the Grameen Bank was providing credit to about 8.3 million people, 97% of who are women, (Grameen, 2016).

²It is critical to note that despite its successes, there is much suspicion around the ability of the schemes to lead the way to sustainable economic development. However, the suspicion is mostly on the programmatic issues of the schemes rather than their rationale, which is providing credit access to the poor.

that they can use to ensure each member pays a jointly liable loan. Therefore, group lending leads to a lower interest rate, which increases loan repayment; as shown by [Varian \(1990\)](#); [Ghatak \(1999\)](#), this is because lower interest rates bring back high-quality borrowers into the credit market, which increase repayments. Hence, group lending enhances loan repayments because joint liability motivates individual members of groups to engage in activities like screening ([Varian, 1990](#); [Ghatak, 1999](#)) and monitoring and enforcement ([Stiglitz, 1990](#); [Besley and Coate, 1995](#)) that minimize the incentive to default. Hence, social structures are essential for the success of the schemes. Accordingly, most of the empirical evidence on group lending and loan repayment or delinquency (e.g. [Wydick, 1999](#); [Hermes et al., 2005](#); [Karlan, 2007](#); [Cas-sar et al., 2007](#); [Ahlin and Townsend, 2007](#)) focuses on the impact of social capital, which affects the impact of the highlighted mechanisms, on the performance of the schemes. This is usually done while controlling for the effect of individual cognitive traits such as income, age, education, religion, among others, which also affect borrowers behaviour.

However, there has not been much focus on the relevance of non-cognitive traits on borrowers repayment behaviour. From a broader sense, such a challenge is not limited to only the study of micro-lending but economics as a whole. In economics, much of the attempts to characterise individual differences in socioeconomic outcomes as sources of differences in behaviour have been centred on cognitive traits ([Borghans et al., 2008](#)). [Almlund et al. \(2011\)](#) argued that there exist significant imbalance in highlighting how cognitive skills might relate to other non-cognitive traits. This is quite intriguing given that there exists significant evidence in personality psychology that personality traits do affect life outcomes (See [Ozer and Benet-Martinez, 2006](#), for details). The limited evidence that is available in mainstream economics is concentrated on the impact of personality trait on the labour market, education, and financial outcomes. Recently, however, there has been an increase in the number of studies that analyses how the behaviour of economic actors can be related to their non-cognitive traits. However, few studies have looked at the effect of traits on behaviour in other markets like credit markets.

Therefore, the central motivation of this study is to contribute to the filling of this gap. In particular, the intention is to add to the evidence on the relationship

between non-cognitive traits and behaviour of borrowers in microcredit markets. I do this by studying how the dispositional aspects of borrowers affect their repayment behaviour. Thus, the study is based on borrowers participating in an NGO grouped based microcredit program in Gambia that targets only women.³ The psychological traits are measured using the Five-Factor model (FFM in short), which is the main instrument used to measure personality traits. In Psychology, there are shreds of evidence that these traits affect human behaviour. Thus, I study the extent to which these traits are capable of predicting borrowers default behaviour; default behaviour is measured through a question in a survey that asks a borrower whether she has once defaulted on her part of a group loan or not (i.e. delinquency in loan repayments).

Therefore, this study is broadly related to a study by [Karlan et al. \(2012\)](#) (from here KMR). In particular, like KMR I also use survey-based measures of personality traits to study individual default behaviour. However, it differs from these authors in two ways: Firstly, unlike their study which is based on borrowers that were participating in an individual microcredit scheme, this study is based on borrowers participating in group lending schemes. Given that the factors that affect behaviour could be different in the two settings, one expect for the dynamics of the relationship between traits and behaviour to be also different in the two types of lending schemes. Secondly, unlike KMR who uses a short BFI inventory to measure personality traits, I used a more extensive BFI inventory to measure traits. In measuring traits, the use of longer rather than "abbreviated" instruments is encouraged because they have a higher Psychometric validity (See [Gosling et al., 2003](#); [Soto and John, 2017](#)).

In a broader sense, therefore, the study will be an addition to the scanty evidence on the impacts of psychological traits on economic behaviour in credit markets; this of particular importance to financial institutions that lend mainly to poor borrowers, who among other limitation do not have credit histories that can be used to gauge their qualification for a loan. Thus, screening based on traits could be useful complements and maybe even substitutes (in some instances) for formal requirements like

³Lot of evidence have shown that when it comes to poverty in developing countries women tends to share a large chunk of the burden. Thus, the program that targets women are likely to have more impact on household welfare than otherwise (See [Buvinić and Gupta, 1997](#), for details).

past credit history, which poor borrowers find challenging to fulfil. Hence, if personality traits are found to be relevant in predicting loan default, a case can be made for them to be part of alternative tools used for addressing asymmetric information problems in microcredit markets. The objective of this paper is not to make such a radical suggestion, but rather to show that psychological traits can reveal information that markets do not reveal and in so doing they could be useful in addressing market failures in credit markets.

The rest of the chapter is structured as follows: following the introduction in section 3.1, section 3.2 discusses the evidence in the literature. In section 3.3, I describe the data collection and sampling technique. The empirical strategy, the issues of identification and sample selection are discussed in section 3.5. In section 3.6, I report and discuss the results. Finally, in the last section, I summarize my main findings and give a conclusion.

3.2 Literature Review

The study of Personality trait is as old as the study of the human language ([Matthews et al., 2003](#)). According to [Almlund et al. \(2011\)](#), Personality is a system of relationships that map traits and other determinants of behaviour into actions. Hence, personality trait is one of the determinants of personality. [Costa Jr and McCrae \(1995\)](#) define personality trait as "the relatively enduring styles of thinking, feeling, and acting that characterize an individual." For this reason, it is widely believed, by personality psychologist and other social scientists, that there exists a relationship between personality traits and a lot of life outcomes such as schooling, employment, and career paths ([Matthews et al., 2003](#)).

Despite abundant evidence in psychology that non-cognitive traits such as those measured by the Five-Factor model affect behaviour, the empirical evidence on the impact of non-cognitive traits on economic behaviour is still limited. Many of the studies in economics on the subject are focused on the impact of personality traits on labor market outcomes and the relationship between personality traits and trusting behaviour or trustworthiness in behavioural games.

In studying the impact of personality trait on household finances in Britain, [Brown and Taylor \(2014\)](#) find that personality traits relating to factors in the Big Factor Model (such as extraversion and openness to experience) correlate highly with personal finances. Similarly, [Donnelly et al. \(2012\)](#) study the relationship between personality traits and money management and find evidence that conscientious individuals are better in money management due to better financial attitudes and future orientation. There is also an extensive (but not in any way exhaustive) strand of literature focused on the relationship between personality traits and behaviour using insights from game theory. For instance, [Boone et al. \(1999\)](#) study (non)-cooperative behaviour in prisoner's dilemma games and the impact of personality traits on the outcomes of the games. They find evidence that personality traits such as internal locus of control, high self-monitoring and high sensation seeking are related to cooperative behaviour. In a similar vein, [Kugler et al. \(2014\)](#) study whether personality traits (such as anxiousness and aggressiveness that are facets of the neuroticism) affect strategic behaviour. They use a two-player entry-level game in which a player gets a guaranteed reward by opting to stay out, gains more when the player is the only one that enters, and gain less when both decide to enter. They find that the level of anxiousness and aggressiveness determines a player's choice to enter or stay out in the game. In particular, anxious players enter less and aggressive players enter more. Also, they find that anxious players were less likely to enter than non-anxious players and aggressive players were more likely to enter than non-aggressive players. [Hammond and Morrill \(2016\)](#) study the impact of personality on bidding behaviour in English auctions with competitive sellers. They find evidence that personality traits measured using the Big Five taxonomy have a significant impact on bidding behaviour for women. [Braakmann \(1999\)](#) use data from the 2005 wave of the German Socio-Economic Panel (SOEP) survey to study the relationship between non-cognitive traits and the difference in the labor market outcomes of men and women. He finds evidence that "psychological traits" have a significant and non-negligible effect on the gender gap in employment and wages.

[Rustichini et al. \(2016\)](#) used laboratory experiments to study the relationship between personality traits and economic preferences. As in similar studies, they also find that there exists a link between personality traits, particularly elements of the

Big Five domains, and economic preferences. Additionally, their results indicate that intelligence and Neuroticism constitute the core links through which personality trait relate to economic preferences. Specifically, they find that intelligence correlates positively with patience and Neuroticism is negatively correlated with the attitude towards risk. Furthermore, their results also indicate that Extraversion is related to aversion to ambiguity and Agreeableness play a significant role in predicting both cognitive and behavioural responses in their setting. Mainly, they find that Agreeableness accurately predicts players beliefs on the action of others; higher Agreeableness scores relate with an inclination to expect more cooperative actors. From their evidence, they concluded that adding non-cognitive measures to many cognitive measures used by economists can significantly increase the predictive power of most dependable variables, especially when these are real-world economic outcomes.

In the microcredit literature, KMR was the only contribution I find where the relationship between personality traits and default behaviour was studied. They used both field experiments and survey methods to collect information on borrower non-cognitive traits, which are then used to predict default behaviour. They find that both individual morality and naivety (measured from the field experiments) do have a significant impact on default behaviour. Specifically, borrowers with high levels of morality are less likely to default and when they do they default with fewer amounts. With regards to naivety, they find that borrows that are more naive about their abilities to repay a loan are more likely to default. Besides, they also studied whether generalised measures of personality traits, such as the elements of the Five-Factor model, can predict default behaviour. They find that such general indicators of non-cognitive traits do not predict loan default, in that in their study none of them was found to have a significant impact on default. They used these pieces of evidence to argue that moral hazard problems are real in micro-lending markets, and also that there are tendencies for the existence of adverse selection problems since personality traits are not observable to the lender.

Hence, the contribution of this study to the above strand of studies is that it uses dispositional aspects of borrowers behaviour to study their default behaviour. As

stated above, the study by KMR seems to be the only study in the microcredit literature that looks at the relevance of such indicators in predicting default behaviour. And given that evidence from other areas of economics, such as behavioural and labor market economics, show that these traits indeed matter for behaviour, implies more evidence on them are required in the microcredit literature. This study is an attempt to fill this gap.

3.3 Sampling

The data was collected via a survey of borrowers participating in a group-based lending scheme of an NGO microcredit provider in Gambia called GAWFA (Gambia Women Finance Association).⁴ GAWFA is among series of NGOs run microcredit programs found in Gambia that were established to fill the gap left by commercial banks in the access to finance.⁵ The NGO is founded in 1987 by the coming together of different women groups whose vision was to tackle the difficulties faced by women in the access of formal financial services such as credit. However, it was in 1997 that it got its license from the Central Bank of The Gambia, the official regulator of microfinance or microcredit institutions in Gambia, to operate as the first micro-credit institution in Gambia that is designed primarily for rural women. Accordingly, about 96% of their existing clients are women, and 90% of them are dwellers of rural communities. Currently, GAWFA is providing financial access to about 14,377 women in 78 communities across the length and breadth of Gambia. As of 2015, its total loan outstanding stood at about GMD 7 million (about \$200,000), making it one of the giant microcredit providers in Gambia. GAWFA offers two forms of group-based lending: Large Group (LG) loan and Solidarity Group (SG) loan.⁶ The LG loans are disbursed to groups of at least 12 members who use the loan for either the income generation activities of the group or to finance members individual income-generating activities. The SG loans, on the other hand, are disbursed to groups of 3-11 members. Most members of the SG loan groups are market vendors or family holders, and the loans are used for their income-generating activities.

⁴In the Gambia, lending programs targeting groups are organised through *Kafoos* or *Compins*. These are "homogeneous group of individuals in a village with mutual interest" (Ouattara et al., 1993).

⁵The introductory section of Ouattara et al. (1993) contains detail discussion of this phenomena

⁶Note that these are terms used by the organisation to define its group lending schemes.

GAWFA does not directly influence the formation of groups by potential borrowers; the client make this decision individually.⁷ The members of a loan group act as guarantors to each other, which make all of them liable for any defaulted loan.

Consequently, a loan remained unpaid unless all the members responsible for the loan repay on time. Considering that the main argument in favour of group-based lending in the microfinance literature is that it reduces asymmetric information problems through joint liability for loans. The joint liability nature of the GAWFA lending program makes it ideal for this study. To recover loans, GAWFA works with credit officers that deal directly with group heads to collect the repayments for a loan; when repayments are collected they were usually recorded in logbooks, but recently GAWFA has developed an online platform where the information about a group (including loan repayments) are recorded.

In selecting borrowers for the study, a multi-stage design is employed. In the first stage, intervention communities with one of the loan schemes as mentioned earlier schemes (LG loan or SG loan) of GAWFA are grouped into four strata given by region. In each region or strata, 3 to 7 intervention communities were randomly selected.⁸ In the second stage, 1 to 3 groups were randomly selected in each intervention community, and all the members of the selected groups were interviewed.⁹ For the respondents selected, interviews were carried out face to face using structured questionnaires that were administered via an enumerator. Three different set of questionnaires were administered during the survey. The first questionnaire collected standard information on a borrower's socio-demographic and non-socio demographic characteristics. Besides, it also collected information on borrowers civic and religious engagement, a perception of trust, fairness, help, and bonding social capital. The second questionnaire collected information on borrowers personality traits, i.e. on the dispositional aspects of a borrower's behaviour. To this effect, a 30 item personality trait instrument, the so-called BFI-2-S (See [Soto and John, 2017](#)) was

⁷I am aware that this could be a source for potential selection bias.

⁸The Randomisation was done using excel. First, random numbers were generated and then they are ordered ascendingly. After the ordering, the first 3 to 7 rows (in the case of intervention communities) and the first 1 to 3 rows (in the case of groups) are selected.

⁹If the enumerator is unable to interview any member of a selected group, then, he has to organise for a recall and the time frame for the recall is 1-7 days. If after 7 days the individual is still not available for an interview, she is considered a nonresponse.

used. This instrument is a brief version of the 44 item inventory of (See [John and Srivastava, 1999](#)) commonly applied in personality psychology. Each item constitutes a sentence containing an adjective that may or may not describe the individual, and the individual is required to rate herself on each item using a Likert Scale from 1 to 5. The third questionnaire was a social network questionnaire, and to answer the questions on this questionnaire, a respondent was provided with a list of all the contacts in her group. She is asked to indicate which contacts in the list came to her for a particular form of advice or help, and also those she goes to for the specific advice or help. For each contact specified, the respondent is also requested to specify the type of relationship she shares with the named person.¹⁰

All the questionnaires, except the social network questionnaire (administered in paper form), were administered using the Magpi CAPI survey tool.¹¹ The interviews were carried out between October and December 2016 by a team of 5 enumerators with a single supervisor (the lead researcher). The enumerators were distributed across the four regions involved in the study and each covered about four villages. An enumerator was mandated to stay in a village until all the groups in the village are covered, and all members of the group are interviewed. To facilitate their work in the field, they were all provided with smartphones and power banks. All enumerators were required to upload all their completed questionnaires onto the Magpi platform daily, which are checked by the supervisor daily. The supervisor's role was to ensure that all questionnaires uploaded were freed of data collection errors that can be corrected in the field, as errors found are supposed to be addressed before an enumerator leaves a village.

Given that most of the respondents are illiterates and with little or no knowledge of the official language, English, all questionnaires were administered in the local language comfortably understood by the respondent.¹² In this regard, enumerators were used that are thoroughly conversant in the language widely spoken in the communities where they were to be sent. Familiarity with the region was also considered

¹⁰The information from the social network question is not used in the current paper.

¹¹Magpi is a leading provider of configurable, cloud-based mobile collection, communication, and data visualisation tools to let organisations improve the effectiveness of their mobile workforce and improve field operations, see <http://home.magpi.com/about/>

¹²Usually this is a language of the dominant tribe or ethnic group in the community where the interview was conducted.

an essential factor for selection. Furthermore, two-day training of enumerators was also done to train enumerators on using the data collection App and administering the survey instruments. Another purpose of the training was to ensure that the enumerators can administer the questionnaires in the local languages.

Regarding the personality trait questionnaire, all trait adjectives used in the inventory were translated into the local language by the researcher via the assistance of a native speaker of the local language and after a backward translation is done to English. If ambiguity arises in the meaning of an English adjective when translated in the local language, about five native speakers are randomly sought and ask about the meaning of the adjective in their local language. Adopted as the appropriate meaning of that adjective in the local language is the most common interpretation given by these respondents. In selecting the enumerators, therefore, I emphasise being a native speaker of the local language to be used in administering the questionnaires and also obtaining credit in English in the high school final examinations. These checks were instituted to ensure that the responses to the questions, especially those in the personality trait questionnaire, are not motivated by poor translation of the questions in the local language of the respondent by the enumerator.

Therefore, from an initial sample of 600 respondents, I got 528 responses, and there were 72 non-responses; they couldn't be interviewed within the recall time frame stipulated. So, the response rate is about 82 per cent. However, about 11 observations were further lost during the data cleaning. Thus, the final sample constitutes 517 individual observations. The total number of communities selected was 18, and about 34 groups were involved, out of which 20 were solidarity groups, and 14 were large groups.

3.4 The Big Five Inventory

In personality psychology, there is a generally agreed notion that only five or six dimensions of personality are the source of much of the variation in human behaviour (Rustichini et al., 2016). Hence, the Five-Factor model, which measures personality by relying on five big dimensions, is the most widely used measure of personality

traits. It involves the grouping of traits into mutually exclusive categories using approaches that originated from the lexical hypothesis; an idea that was first used by [Galton \(1884\)](#). It is based on the premise that the most important traits in people lives can be expressed as single terms in their common language ([Goldberg, 1993](#)). Hence, a good starting point for a "shared taxonomy is the natural language" ([John et al., 2008](#)). The idea that personality traits can be studied by grouping traits into mutually exclusive categories using terms from the common language came from the contributions of German psychologist [Baumgarten \(1933\)](#) and [Allport and Odbert \(1936\)](#).¹³ The contribution of the former was stimulated by the work of another German Psychologist [Klages \(1926\)](#) who first hinted that the careful analysis of language could help in the understanding of personality traits ([Digman, 1990](#)). The finding of these authors laid the ground for a common taxonomy of personality traits and the emergence of personality trait measures such as FFM.

The Big orFive-Factor model involves the grouping of personality traits into five main domains, namely: Extraversion, Neuroticism, Openness to Experience, Conscientiousness, and Agreeableness. For the sake of preciseness, each of these domains could be further divided into facets. The development of the Five-Factor model of personality started with [Thurston \(1934\)](#) and Raymond Cartell (See [Cattell, 1943](#)). It was developed further by several authors (such as [Norman, 1963](#); [Digman, 1963](#))). [McCrae and Costa Jr \(1985\)](#) built on the work of the previous contributors, particularly [Eysenck \(1970\)](#) who first introduced Neuroticism and Extraversion, and created a variant of the personality factor model called the NEO (for Neuroticism, Extroversion and Openness to experience; respectively) personality instrument. In [Costa and MacCrae \(1992\)](#), the NEO instrument was revised to include two more factors (Conscientiousness and Agreeableness) to make it a standard Five-Factor personality inventory (See [Goldberg, 1993](#), for more elaboration.)

Each of the domains constitutes many traits ([Goldberg, 1993](#)). Extraversion measure how energetic an individual is and to what extent is the individual engaged with the world, as well as the individuals' social attitude. Hence, it can be viewed as a contrast between traits such as activity level, assertiveness and talkativeness and traits such as being passive, reserve, and silence ([Goldberg, 1993](#)). Neuroticism

¹³(See [John et al., 2008](#)) for details.

measures emotional instability, that is, the tendency of an individual to experience negative feelings or other forms of emotional discontent such as anxiety, anger, or to suffer from stress. Therefore, it constitutes traits such as nervousness, moodiness, not contented, shyness, and not self-confident. Openness to Experience measures the extent to which an individual is curious, imaginative, and appreciates new and unconventional ideas, as well as, being aesthetic or having passionate feelings. Conscientiousness is a measure of whether an individual has a future orientation or not. Hence, it includes traits that capture things like competence, orderliness, dutifulness and deliberation and also self-discipline. Agreeableness measures the ability and tendency of an individual to cooperate with others as well as the individual's level of altruism. It involves facets that measure cooperative behaviours such as trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness.

To measure the elements of the BFI, I follow the approach of [Goldberg \(1990\)](#).¹⁴ Specifically, the BFI I use consists of 5 domains (as outlined above) and each domain or element of the BFI is further divided into an average of 6 personality facets or items.¹⁵ Therefore, the BFI inventory used here is an abbreviated version of the 44 item BFI found in [John and Srivastava \(1999\)](#).¹⁶ There is evidence (e.g. [Soto and John, 2017](#)) supporting psychometric validity of brief BFI inventories. Hence, due to the fear of not to bore interviewees with lengthy questionnaires, many researchers (particularly in economics) opt for a shorter rather than a long personality trait instrument. However, the fact that long instruments have better psychometric features than small instruments ([Gosling et al., 2003](#)), they should be preferred when it is ideal. It is for the latter reason that I decided to use a longer instrument here.

As indicated in the previous section, the data was collected by asking each to rate herself on each of the 30 items of the BFI inventory using a five-point Likert scale ranging from 1 (disagrees strongly) to 5 (Agrees strongly); the questionnaire is reported in the appendix. Then, the individual score in each domain is computed

¹⁴The primary difference between [Goldberg \(1990\)](#) BF instrument and other similar instruments of the Five-Factor model is that he assumed that the warmth facet captures more Extraversion than agreeableness. Therefore, warmth is categorised in the Extraversion group.

¹⁵Note that the number of items and facets are the same in my case because I am using one item per facet. This need not to hold always.

¹⁶This method of constructing the FFM was first proposed by [Costa and MacCrae \(1992\)](#) and is widely known as the NEO-PI-R (that is the revised NEO Personal Inventory).

by averaging her score on all the items that constitute that domain. As different sub-groups have a different number of items, I standardised the scores around mean zero and standard deviation one; so, only the standardised scores are used in the analysis. Given that scale based measures are used to collect information on variables that cannot be measured explicitly, it is a good practice to check for internal validity of these measures; to this effect, reliability measures such as the Cronbach's alpha or factor analysis are employed. In this regard, I checked for internal consistency of the elements of the BFI using the Cronbach's alpha.¹⁷ The results indicate a reliability index that ranges from 0.63 for Openness to Experience to 0.75 for Conscientiousness. The reliability indexes I obtained are less than those found by [John and Srivastava \(1999\)](#); he reported that the reliability indices for the 44 item BFI scales is between .75 and .90. The difference could be driven by the fact that I am using a brief instrument.¹⁸

3.5 Empirical Strategy

3.5.1 Model

Given that the main outcome variable of interest is binary, a simple logistic model was used to estimate the impact of personality traits on the repayment behaviour of borrowers. In the literature loan default is the primary variable that is used to capture repayment behaviour. It is, therefore, the most focused on outcome variable for researchers and practitioners ([Karlan, 2007](#)). But in my case, I do not have a data on group loan defaults as the credit provider does not have a proper record of this data for the clients. Furthermore, given that I am interested in individual default behaviour, I use delinquency - measured by a borrower's self-report of whether she once fail to repay a loan on time or not - as a proxy for individual borrower's default. This variable is coded as one for individual who reported that they have not paid a past loan on time and zero otherwise. As such a measure of default is somewhat subjective, all self-reports were verified from the group heads; one might wonder

¹⁷([Bland and Altman, 1997](#)) provide a brief and comprehensive introduction of the Cronbach's alpha.

¹⁸See [Mueller and Plug \(2006\)](#) for an explanation of how the number of items affects the reliability index of a measure.

why to verify through the group heads and not the credit officers. The motivation behind this is two-fold: first, the group heads are usually responsible for collecting individual repayments and hands them over to the loan officer who records the payment immediately on the GAWFA online loan recovery platform (before used to be on a loan recovery book) and gives the head, on behalf of the group, a receipt of repayment. Thus, the group heads are more informed about individual late repayments than the loan officer. Second, it sometimes occurs that an individual fails to repay on time, but this is unknown to the loan officer as the group repays on time; this happens when the group head or some other member(s) of the group pays on behalf of a defaulted member to ensure that the group repays on time.

Therefore, on the right side of the logistic model, I have the personality trait variables (measured using the Five-Factor model) and control variables. The personality traits are Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience. There are two sets of control variables: One set controlling for individual differences in social capital and the other set controlling for individual differences in cognitive traits such as age, education, marital status, and ownership of a business or income from an owned business. The inclusion of social capital variables as a control variable is motivated by evidence in the group lending literature (e.g. [Cassar et al., 2007](#); [Ahlin and Townsend, 2007](#)) that social capital affects repayment behaviour. For this reason, I also include social capital variables to see the extent to which they matter for default behaviour in a model with borrower's personality trait indicators.

Social capital is measured by asking respondents five questions around their bonding social capital, which are reported on a Likert scale from 1 (it does not apply to me) to 5 (it very strongly apply to me). Specifically, the five questions that measure bonding social capital are: "I live in a close-knit neighbourhood," "People in neighbourhood are generally willing to help their neighbours," "People in my neighbourhood don't like each other," "People in my neighborhood share the same value," "People in my neighborhood can be trusted." The latter method of measuring bonding social capital was first used by the Project on Human Development in Chicago Neighborhoods (PHDCN) ([Usher, 2005](#)). The individual scores on the five items are averaged for each respondent to obtain an index that captures their social

capital, which is called socindex in the dataset. Again since the measure is collected from self-reports using Likert scales, it is recommended to check for its construct validity using a reliability index. As for the personality indicators, a Cronbach's alpha is used for this purpose. The results are reported in Table 3.1. It can be seen that the reliability index of the measure is about 0.69, which is acceptable. The standardised score has a minimum value of -3.84 and a maximum value of 1.73. Another method of measuring social capital that is commonly employed in the group lending literature (e.g. in [Karlan, 2005](#)) is using three questions from the Generalized Social Survey (GSS in short) that captures individual perception on "trust," "fairness," and "helping" as a measure of social capital. There is proven evidence that perception on these items is significantly related to real-world outcomes ([Karlan, 2005](#)). Hence, I also included them in my survey to check whether they affect the repayment behaviour of the borrowers studied. In other words, whether such general measures of social capital used in a developed country context can also capture social capital in a developing country context. All the two measures of social capital are included in the model as an index. That is they are pooled into a single measure, which is used for the analysis; this was done by summing the respondent's reported score on each of the items and then standardising this around mean zero and standard deviation one. Note that for GSS measure of social capital I also checked its reliability index; this is reported in Table 3.2. The alpha coefficient of the measure is 0.77, and the standardised scores have a minimum value of -2.94 and a maximum value of 2.30; even though not that high, it is also acceptable.

Therefore, the logistic model to be estimated can be summarized as follows:

$$\text{logit}(y_i) = \alpha_1 + \sum_{i=1}^{P=5} \beta_{1i}x_{1i} + \sum_{i=1}^{Q=2} \beta_{2i}x_{2i} + \sum_{i=0}^{C=7} \beta_{3i}x_{3i} + \epsilon_i \quad (3.1)$$

Where x_{1i} denotes a set of $P = 5$ variables constituting of the 5 personality traits variables from the BF model, the x_{2i} denotes a set of $Q = 2$ variables that measure the social capital variables, and x_{3i} denotes set $C = 7$ control variables that measure the cognitive traits of the borrower. The variable y_i is the dependent variable representing the odd ratio of not repaying a loan, which is measured from borrowers self-reports on their past default. It is coded 0 if the individual reports that she has

TABLE 3.1: Reliability Index of Social Capital Index

Interim Correlations-Crohnbach Alpha					
	knit	aidneig	hate*	samval	trust
Knit	1.00				
Aidneig	0.34	1.00			
Hate	0.26	0.41	1.00		
Samval	0.12	0.18	0.27	1.00	
Trust	0.30	0.50	0.34	0.07	1.00
Alpha					0.69

* The scales on this measure are reversed.
See table 2 for the description of variables.

TABLE 3.2: Reliability Index of GSSindex

Interim Correlations-Crohnbach Alpha			
	GSS1	GSS2	GSS3
GSS1	1.00		
GSS2	0.56	1.00	
GSS3	0.49	0.53	1.00
Alpha			0.77

never defaulted on a past loan and 1 if the individual reported that she has once defaulted on a past loan. Note that default here means the individual was not able to repay a loan on time; hence, it is a measure of delinquency and not actual default. Consequently, a shortcoming of this measure is that it does not directly measure the repayment performance of a group, as individual late repayment does not necessarily lead to group default. However, if it (late repayment) is rampant in a group it could affect group performance; that is many group members not being able to repay on time could force a group not to repay on time. Indeed, the measure can be a proxy of how individual behaviour might affect group outcomes and consequently the performance of a group-based lending scheme; having said that it is important to note that in this study the focus is on individual default behaviour and not on group default. Another shortcoming of the measure is that it is based on self-reports by

the borrower, which tend to be subjective. However, in reference to [Petrick \(2005\)](#), [Dufhues et al. \(2012, 2013\)](#) highlighted that no "plausible argument" exist to presume that subjective information are less valid than other information in survey data. In this regard, even if subjectivity of the measure could be a concern, no proper evidence exist to suggest that this will invalidate the measure of default. Moreover, given that self-reports by the borrower were further verified from the group head, who collect individual repayments, increases the validity of the measure.

In estimating the model, three different specifications are used: The first specification is a model with just the critical core variables. In the second specification, the variables that measure trust and bonding social capital are added to the first specification to capture the effect of social capital on default behaviour. In the third specification, the cognitive trait variables are added, as control variables, to the second specification. The essence of these three specification is to see how the addition of additional explanatory variables to the critical core variables changes the logistic regression results as well as to see the relevance of model specification.

In all estimations, cluster effects (clustering at the group level) were controlled for, and standard errors were estimated using the jackknife method; [Quenouille \(1956\)](#) first introduced this method, and extended by [Tukey \(1958\)](#) for variance estimation. As a nonparametric repeated sampling technique, the jackknife method is similar to bootstrap with the advantage that it is more robust in small samples (See [Efron and Stein, 1981](#)). Given that only 34 groups are involved in the study implies the study consist of 34 clusters and resampling is done in these clusters; this is the motivation of using the jackknife resampling technique. All estimations were done in STATA 14, and I used the svy command to capture the survey design in the estimations.

3.5.2 Identification Issues

In relating default behaviour to individual borrower's characteristics, [Karlan \(2007\)](#) has highlighted two identification concerns that are due to peer-selection by borrowers into borrowing groups; omitted variable bias and simultaneity bias. Omitted variables bias arises because self-selection means individual join groups based on characteristics that are not observable to the researcher, which could correlate with

both the observed characteristics as well as group outcomes. Simultaneity bias, on the other hand, arises when the relationship between individual characteristics and group outcomes can be inferred in both directions.

A good example is where successful groups lead to better social relations; hence, the direction of causation between group outcomes and social relations occurs in both ways, thus, making causal inference ambiguous (See [Karlan, 2007](#), for detail discussions). Therefore, given that social capital variables were added in specification II and III, simultaneity bias could be a concern in these models. But, the good news here is that the measures employed to collect data on social capital were based on generalised perception on trust or help or fairness, and there is evidence that generalised perceptions on trust and help are determined by village level outcomes that are independent of individual or group level outcomes. In this sense, these measures of social capital can be regarded as exogenous. For this reason, I do not worry about the problem of simultaneity bias for my social capital variables.

Simultaneity bias could also arise from the personality trait variables. To see why, assume that borrowers with a higher level of non-cognitive traits are more likely to join high performing loan groups. In this case, it is not far-fetched that personality traits affect repayment behaviour and that repayment behaviour can also affect the borrowers observed level of personality traits. This potential for simultaneity bias mainly arise when individual personality traits are not stable in that group level outcomes can impact them over time. To this effect, however, there exist numerous evidence that personality traits are stable over time. For instance, [Conley \(1985\)](#) find that "there is a set of personality traits that are generalisable across methods of assessment and are stable throughout adulthood." Using a meta-analysis approach, [Roberts and DelVecchio \(2000\)](#) study the stability of traits across different age groups, and find that while the stability of personality traits varies across different age groups, over a 6.7 year period, they tend to be stable in adults. In particular, he finds that for individuals between age 50 and 70 the stability of traits reaches up to 0.74 on a 1.0 maximum scale. [Cobb-Clark and Schurer \(2012\)](#) used data from Australian households to study the stability of adult personality traits. They find that the mean level change in personality traits (measured using the BFI model) of adults between age 25 and 64 "are small and do not vary substantially across age

groups." Other evidence on the stability of noncognitive traits for adults is reported in (Aschwanden et al., 2017; Elkins et al., 2017; Mosca and Wright, 2018). Using these evidences on the stability of personality traits over time, I conjecture that group outcomes are unlikely to change borrowers individual personality trait levels over time; consequently, I do not expect for traits to be endogenously determined. Such a stand on the exogeneity of personality traits is not new; it is commonly used assumption in researches that study the impact of personality on labour market outcomes (See Viinikainen et al., 2010).

Additionally, I also checked whether personality traits are an essential determinant of the likelihood to join groups by doing the following: first, I determine whether an individual participates in any of the following other three groups - religious, political, and other loan groups. Second, the personality trait variables are related to the probability of joining these groups to check if any significant relationship exists. If a significant relation exists, one could conclude that personality traits are essential factors for joining these groups, and therefore could also be a source of bias for group selection. When this is not the case, then, there is weak evidence that traits might not be relevant for group selection including the decision to join loan groups. The underlying assumption of this exercise is that if traits are relevant in group selection, then, I should observe a positive association between personality traits and the probability of joining a group. The results of this estimation are reported in Table C.1 in appendix C. Controlling for possible confounds, I find that none of the personality traits has a significant (at the conventional level of significance of 5%) effect on the probability of joining other groups. I use this as naive evidence that omitted variable bias due to peer selection is not a fundamental problem in this context.

3.5.3 Sample Selection Bias

Since default behaviour, the outcome variable of interest, is observed only for participants who have received a loan, this might be a source of unobserved selection. In particular, suppose that those that are less(more) credit worthy are more(less) likely to request for a loan. If such unobserved self selection correlates with default behaviour and is not modelled, it will bias the regression estimates. For this reason,

to check for whether this phenomena exists in the data, I used a sample selection model of the form suggested by (Heckman, 1979), also called the Heckman two-step procedure or Heckit estimator (See Cameron and Trivedi, 2005, p. 550).

Specifically, suppose the outcome of interest (loan default) is denoted by y^* and L^* denotes the likelihood of receiving a first loan. Thus, while L^* describes the decision of whether or not to take a loan, y^* describe the decision of whether to repay or not repay the loan. Therefore, given that there are factors (e.g. whether a borrowers is a recipient of international remittances) that are more silent determinants of the decision to take a loan than the decision to repay it, it is apparent that L^* and y^* might not be the same. Thus, the sample selection model comprises of participation equation given as:

$$L = \begin{cases} 1, & \text{if } L^* > 0 \\ 0, & \text{if } L^* \leq 0 \end{cases} \quad (3.2)$$

and an outcome equation of the following:

$$y = \begin{cases} y^*, & \text{if } L_1^* > 0 \\ -, & \text{if } L_1^* \leq 0 \end{cases} \quad (3.3)$$

Hence, y is observed only when $L^* > 0$. Therefore, as demonstrated by Van de Ven and Van Praag (1981), I can specify the unobserved index of the likelihood to take a loan (L^*) as:

$$L^* = \alpha_2 + \sum_{j=1}^{j=3} \beta_j Z_{ji} + \mu_{1i} \quad (3.4)$$

With Z_{ji} a set of $j = 3$ exogenous variables that are determinants of the probability of selection for the i th borrower, β_j is a $j = 3$ unknown parameters, and $\epsilon_{1j} \sim N(0, 1)$. The outcome model for the entire sample from equation 3.1 can be written in vector form as follow:

$$y_i = x_i \beta + \mu_{2i} \quad (3.5)$$

With x_i being a (15X1) vector of covariates as defined in equation 3.1 above; β is a

(15X1) vector of parameters with $x_0=1$, and $\mu_{2i} \sim N(0, 1)$. For the sample of borrowers that have taken a loan, equation 3.5 is given as $y_i = (x_i\beta + \mu_{2i}|L^* > 0)$. Assume that the correlation between μ_{1i} and μ_{2i} is given as ρ and that $\mu_{2i} = \rho\lambda(Z'\beta) + \varepsilon$. Heckman (1979) has shown that if ρ is not zero, then, an OLS or probit estimate of the β s from the model of equation 3.5 using data from just the sample that took a loan is bias (For more on this, see Van de Ven and Van Praag, 1981). Thus, a Heckit approach can be used to correct for such bias. This involves first using a probit model to estimate the β s in the selection equation to get an estimate of the inverse mill ratio $\lambda(Z)$, which is used in a second stage model to get consistent estimates of the coefficients of the main model of interest (See Cameron and Trivedi, 2005, p. 550). Note, however, that if the personality trait indicators are endogenous, then, the two-stage approach will be inappropriate as one of its fundamental assumptions is that the regressors in the main equation are exogenous (See Wooldridge, 2010, p. 813-14). For reasons discussed in section 3.5.2, I do not worry about this problem. Also, note that a test of $\rho = 0$ is a test of sample selection. Thus, I use this approach to test for the existence of a sample selection in the data. The results are discussed in the next section.

3.6 Analysis of Empirical Results

Table 3.3 reports the descriptive statistics of the critical core variables and the social capital variables for defaulters and non defaulters. The critical core variables are domains of the BFI discussed in details in section 3.4, i.e. Agreeableness, Extraversion, Neuroticism, Conscientiousness and Openness to Experience. Note that the summary statistics of the critical core variables reported in Table 3.3 are based on the unstandardised values of the variables. The results show that, except for Neuroticism, the mean score on each of the domains of the BFI is higher for non-defaulters than for defaulters. However, only the difference in the mean score of agreeableness is significant at 95% confidence level. The mean difference in Extraversion and Openness to Experience are significant only at 90% confidence level, and for Conscientiousness and Neuroticism, the difference in means between the two groups is not significant. Also, the results indicate that the individuals or borrowers that repay

TABLE 3.3: Summary Statistics: Critical Core Variables and Social Capital Variables

	Never Defaulted		Once Defaulted		Sign. of Mean Diff. p-values*
	mean & std error	std. dev. & no. of obs	mean std error	std. dev. & no. of obs	
ExTra	9.22 (0.14)	4.21 <i>n</i> = 294	8.66 (0.16)	4.17 <i>n</i> = 129	0.08
AgRea	14.54 (0.22)	3.35 <i>n</i> = 294	13.48 (0.27)	3.80 <i>n</i> = 130	0.01
ConSci	13.11 (0.29)	3.92 <i>n</i> = 291	12.88 (0.28)	3.99 <i>n</i> = 130	0.65
NeuTis	2.14 (0.17)	3.68 <i>n</i> = 294	2.19 (0.23)	4.34 <i>n</i> = 130	0.44
Open	22.71 (0.16)	4.55 <i>n</i> = 293	22.01 (0.19)	4.18 <i>n</i> = 130	0.08
Socindex	20.30 (0.11)	2.70 <i>n</i> = 296	19.06 (0.17)	3.47 <i>n</i> = 130	0.00
Gssindex	0.53 (0.04)	1.10 <i>n</i> = 296	0.07 (0.04)	1.18 <i>n</i> = 130	0.00

Note: For each variable, the table reports the mean, the Jackknife standard error of the estimate of the mean, the standard deviation, and the number of observations in each sub-sample used to obtain the summary statistic. Also reported are the p-values from a t-test of a statistical significance of difference in means between the two groups. The statistics here are calculated from the unstandardised values of the variables.

* The p-values reported are the two tailed test p-values.

on time have a higher mean score on bonding social capital than those that do not repay on time, and the difference in means between the two groups on social capital is highly significant.

The characteristics of the borrowers in the sample are reported in Table 3.4, which also contains brief description of all the variables. For the borrowers in the final sample, about 83% have reported that they have already received their first loan from GAWFA. More than 70% of the borrowers are participants in LG loan schemes. The average of the loan taken is about 2561 Dalasi (about \$60), and more than 50% of the borrowers have received at least this amount from the last loan taken. Among those that received a loan from GAWFA, about 31% have reported that they have once defaulted on a pass loan. The average age of the borrowers in the sample is about 41 years, and about 38% are above the mean age. Only 25% of the borrowers

TABLE 3.4: Summary Statistics: All Variables

	Mean	Std. dev.	N
Dependent Variable			
paid= Did you always pay your loan on time? (yes=0, no=1)	0.31	0.46	426
Independent variables			
<i>Core critical variables</i>			
ExTra= Extraversion	9.27	4.13	513
AgRea= Agreeableness	14.22	3.50	514
ConSci= Conscientiousness	13.34	3.94	511
NeuTis= Neuroticism	1.97	3.91	514
Open= Openness to experience	22.67	4.38	513
<i>Social Capital Variables</i>			
Gss1= People can be trusted	0.31	0.84	517
Gss2= People try to be fair	-0.18	0.88	517
Gss3= People are helpful	0.25	0.87	517
Gssindex*	0.37	1.15	517
Knit= Lives in a close knit neighborhood	4.49	0.84	517
Aidneig= Neighbors helpful to one another	4.50	0.94	517
Hate= Neighbors don't like each other	2.60	1.09	517
Samval= Neighbors share same value)	2.23	2.30	517
trust= Neighbors are trustful	4.41	1.09	517
Socindex**	20.02	2.87	517
<i>Other Control Variables</i>			
Married= Marital status(married=1, not married=0)	0.87	0.48	517
Age	40.59	14.29	513
Educa= Attended school (yes=1, no=0)	0.25	0.43	517
Yedu= Year of education	7.23	3.99	128
lonval= Value of last loan	2561.00	2861.72	400
Ownbuz= Ownership of business (yes=1, no=0)	0.57	0.50	517
<i>Other variables</i>			
Reloan= Received first loan(yes=1, no=0)	0.83	.38	517
Fabrdr= Has a family member abroad(yes=1, no=0)	0.50	0.50	517
Grotyp = Group type (LG=1, SG=2)	1.28	0.45	517

* The gssindex is calculated as the average score of the responses to gss1, gss2, and gss3. Note in the estimation we use the standardized score of the sum of the three, which are denoted with the subscript a1 added to the names.

** Like the gssindex, the socindex is also computed as the average score of the responses to the five bonding social capital questions. The response range from 1 (disagree strongly) to 5 (agree strongly), and the response scales for hate are reversed.

have attended any form of formal education. The rate of business ownership among borrowers is about 51%. The majority of the business owners, more than 60%, are engaged in petty trading including the selling of agricultural produce.

3.6.1 The Effect of the Big Five on Default Probability

Table 3.5 reports the results from the logistic regression specified in equation 3.1. As discussed in section 3.5.1, the logistic model is estimated using three specifications. The first specification is estimation of a model of default behaviour with just the critical core variables. In the second specification, the social capital variables are added to the core variables of interest to control for the effect of social capital on default behaviour. The third specification is obtained by adding the other cognitive trait variables to the second specification. Given that these last model is the richest of the three, it is the main specification of interest. The results of each of the specifications are reported, respectively, as Spec I, Spec II, and Spec III in the table. Generally, the results show that controlling for social capital and cognitive trait variables improve the results; specifically, the log likelihood of the model improves with the addition of more variables to the critical core variables. As expected, a log likelihood ratio test (results not reported) indicate that specification three is a better specification. For this reason, the discussions here are based on the Spec III of Table 3.5.

Except for Conscientiousness, the results indicate that all the domains of the measure of personality traits have a negative effect on the probability of default. In particular, Extraversion is associated with a decrease in the predicted probability of default, and it has a weak statistical significance of 10%. Hence, borrowers that are more sociable and active are less likely to default than borrowers who score low on these traits. As expected, a higher level of Agreeableness, which captures cooperative and trusting attitudes, is associated with a decrease in the predicted probability of default, and this is statistically significant at 5%. Conscientiousness increases the predicted probability, but unlike the other traits it is not statistically significant. Given that conscientiousness measures trait such as being hardworking or organised or resourceful, it is surprising that having such characteristics have a positive predictive probability on default.

A higher level of Neuroticism is also negatively associated with the likelihood of default, and it is statistically significant at 5%; hence, individuals that are emotionally unstable are less likely to default. This result is somehow intuitive as it implies individuals who know that they can quickly get depressed or angered by the action

TABLE 3.5: Borrowers Default Behavior

	Dependent Variable: Individual Default		
	SpecI	SpecII	SpecIII
ExTra _{a1}	-0.149*** (0.038)	-0.140*** (0.032)	-0.054* (0.044)
AgRea _{a1}	-0.353*** (0.071)	-0.231*** (0.075)	-0.228** (0.081)
ConSci _{a1}	0.110 (0.089)	0.061 (0.084)	0.004 (0.082)
NeuTis _{a1}	-0.125* (0.066)	-0.130* (0.069)	-0.173** (0.075)
Open _{a1}	-0.119** (0.052)	-0.049 (0.048)	-0.080* (0.044)
Socindex		-0.096*** (0.017)	-0.102*** (0.019)
Gssindex		-0.337*** (0.047)	-0.320*** (0.051)
Education			0.428*** (0.071)
Ownbuz			-0.063** (0.221)
Age			-0.014*** (0.003)
Married			0.037 (0.200)
Grotyp (SG)			0.810** (0.281)
Memlo			0.193*** (0.0658)
Pseudo R ²	0.03	0.06	0.11
LogL	-251.38	-242.66	-230.51
N	419	419	419

*** 99% significance; ** 95% significance; *90% significance.

Note: Reported in parenthesis are the jackknife standard error that corrects for clustering at the group level. Spec I = logistic regression with just personality trait variables; Spec II= logistic regression with personality traits variables and social capital variables; Spec III = logistic regression with all variables including cognitive trait variables. LogL= Log likelihood and N= number of observations. All the personality trait variables are standardized. Memlo = Whether respondent is member of other loan groups.

of other towards them when they do not repay their debts on time are more probable to repay on time. The explanation could be that they repay on time because they do

not want to face the negative social consequences that come with late repayments. Notice that the coefficient of the Neuroticism variable in specification I (without social capital variables and other controls) is negative and significant in Table 3.5, even though the descriptive statistics reported in Table 3.3 indicate that it is higher for delinquent borrowers. Thus, at first glance this result seems a bit puzzling. However, it could be explained by the fact that I use the standardised scores rather than the level scores of the personality variables in the regression analysis. Moreover, also note that even though controls (other variables different from personality traits) are not included in specification I, this specification contains other personality trait variables different from Neuroticism. Hence, this might be another reason why the coefficient of the Neuroticism variable changes sign and is significant in specification I.

Also, I find that Openness to Experience is associated with decrease in the probability of default, which is also statistically significant at 10%. The negative relationship between default and Openness to Experience is consistent with the a priori expectation. When you are a business owner, true for more than 50 per cent of the borrowers in the sample, then, Openness to Experience could mean willingness to take a risk. There is extensive evidence in the finance and management literature that willingness to take risk is positively related to business success. For this reason, a high level of Openness to Experience should be associated with a decreased probability of default, which is what I find. The marginal effects of the variables on the default probability are reported in Figure C.1 in appendix.

In discussing the results, so far I focus on just the signs of the coefficients from the logistic regressions; this is because the meaning of the magnitude of the coefficients of a non linear model are not clear cut. In this regard, I also computed the average marginal effects (AMEs), which are reported in Table 3.6. The magnitudes of the AMEs have more meaningful interpretation than the coefficients. For the analysis, like before I focus on specification III of the logistic model. Therefore, the results indicate that a standard deviation increase in Extraversion reduces the predicted probability of default by 3% and this effect is statistically significant at 1%. A standard deviation increase in the participants level of Agreeableness decreases the participant's likelihood of not repaying her loan by about 4%. For Conscientiousness, a

TABLE 3.6: Borrowers Default Behavior: Average Marginal Effects

	Dependent Variable: Individual Default		
	SpecI	SpecII	SpecIII
ExTra _{a1}	-0.031*** (0.007)	-0.028*** (0.006)	-0.027*** (0.008)
AgRea _{a1}	-0.073*** (0.009)	-0.045*** (0.011)	-0.036** (0.011)
ConSci _{a1}	0.023 (0.014)	0.061 (0.066)	0.007 (0.012)
NeuTis _{a1}	-0.130** (0.052)	-0.026** (0.010)	-0.028** (0.010)
Open _{a1}	-0.024** (0.010)	-0.049 (0.044)	-0.010 (0.007)
Socindex		-0.096*** (0.013)	-0.041*** (0.009)
Gssindex		-0.337*** (0.047)	-0.059*** (0.010)
Education			0.083*** (0.021)
Ownbuz			-0.119*** (0.025)
Age			-0.003*** (0.001)
Married			-0.007 (0.033)
Fabrd			-0.001 (0.017)
Grotyp (SG)			0.161** (0.032)
Memlo			0.318 (0.1079)
N	419	419	415

*** 99% significance; ** 95% significance; *90% significance.

Note: Reported in parenthesis are the jackknife standard error that corrects for clustering at the group level. Spec I = Model with just personality trait variables, Spec II= model with personality traits variables and social capital variables, Spec III = Model with all variables including cognitive trait variables. All the personality trait variables are standardized. Memlo = whether participant is member of other loan groups.

standard deviation increase in the trait increases the predicted probability of default by 0.7 percent. It is the only trait variable that increases the probability of default, but it is not statistically significant. Like Extraversion, a standard deviation increase

in Neuroticism reduces the participant's probability of default on a loan by about 3 percent and the effect is also statistically significant. Increase in Openness to Experience is associated with about 1 percent decrease in the probability of default, but is not statistically significant. Therefore, among the personality trait measures, Agreeableness has the highest impact on the probability of default.

3.6.2 The Effect of Cognitive Traits on Default Probability

The estimation results on the predictive power of the cognitive trait variables on the probability of default are reported in Table 3.5. Explicitly, the results indicate that being educated is positively associated with the probability of default and it is highly statistically significant. The AME of educations on the probability of default is about 0.08, thus, implying that educated participants are 8 percent more likely to repay their loans than non-educated participants, which is against the *ex ante* expectation. A priori we expect higher human capital levels, an indication of the level of productivity, to be negatively associated with loan default; i.e. more productive borrowers (measured by education level) are more likely to invest their loan more productively (See [Ahlin and Townsend, 2007](#)). Notwithstanding the a priori expectations, the result on the impact of education on loan default has been mixed (See [Hill et al., 2012](#)); some empirical studies find positive effects and others find negative effects. Concerning why education might relate positively with loan default, two explanation could be given: first, it could be motivated by the fact that education is negatively related with informal business (See [Jimenez et al., 2015](#)), and in developing countries, informal business is more rampant. Thus, when money is borrowed, and it is not used to set up or bolster an informal business then it is more likely to be spent unproductively, which reduces the probability of repaying it. Second, as explained in detail in [Hill et al. \(2012\)](#), it could be that education is negatively correlated to credit rationing or that it is positively correlated with outside credit options. These factors put together imply that educated borrowers are less worried by the performance of group loans, and therefore they usually don't mind defaulting on such loans. Like in [Hill et al. \(2012\)](#), my findings support this latter view.

As expected, owning a business decreases the probability of default. In terms of AME, Table 3.6 shows that borrowers that own a business are about 12 percent

less likely to default on a loan than borrowers that do not own a business. Given that owning a business is akin to the productive use of a loan, it should not be far-fetched that it reduces the probability of default. I also find that age is negatively related to default probability, and it is highly statistically significant. In particular, an additional year increase in age of the borrower results to about 0.3 percent statistical significant decline in the borrower probability to default on a loan. Hence, older borrowers are more likely to repay their loans on time than younger borrowers. A similar finding is reported by [Mokhtar et al. \(2012\)](#), and they provided two explanations for this: one, older borrowers are more experience in business than younger borrowers; hence, they are less likely to face repayment difficulties associated with business failure. Two, being young increases the believe that you can get a loan from another microcredit provider even if you once defaulted with other providers. Another explanation of this phenomena could be that older women see their microcredit loans as the only source of external financing to bolster their business while young women have other means of external financing; that is they have stronger outside options (such as relying on parents or other family members for financial support) than older women.

With regards to group size, the finding is that being a member of a small group increases the probability of not repaying a loan on time, and the effect is highly significant. The AME of group size shows that borrowers in sodarity groups (i.e. small groups) are 16 percent more probable of not repaying their loans on time than borrowers in large groups. This finding is in contrast with the evidence in the literature (e.g. [Abbink et al., 2006](#)) that larger group size is associated with more loan repayment problems. Due to moral hazard problems, as group size increases peer monitoring becomes more costly, thus, increasing default probability. However, [Ahlin \(2015\)](#) have theoretically demonstrated that depending on the amount of social capital that exists within groups, under adverse selection, higher group size leads to higher loan repayment. In this regard, the impact of group size on loan repayment is not clear-cut. But the results obtained here are consistent with [Ahlin \(2015\)](#). Table 3.6 indicate that married borrowers are 0.7 percent more likely to default than non-married borrowers, but the effect is not statistically significant.

For social capital variables, Table 3.5 shows that both the measure of bonding

social capital and the GSS measure of social capital are associated with negative default probability and are highly significant. Specifically, the average marginal effects imply that for social capital measured via the GSS index, a unit increase leads to 6% statistically significant decline in the probability of default. A unit increase in bonding social capital decreases the probability of default by about 4% and is statistically significant. Therefore, consistent with the evidence in the literature, briefly discussed in section 3.5.1, I also find evidence that higher social capital motivates higher loan repayment; this finding about social capital is almost a stylized fact in the group lending literature.

3.6.3 Selection Bias

As highlighted in section 3.5.3, since information on repayment behaviour is collected on just participants that have once taken a loan, this could result to sample selection problems. For this reason, I check for possible selection bias by using the approach described in section 3.5.3. In particular, I use Heckman two step approach to test for the presence of sample selection bias in the data. In the first stage, a binary model of the probability of taking a loan (i.e. equation 3.4) is estimated; this first stage regression is used for getting the β s and inverse mill ratio (i.e. $\lambda(Z'\hat{\beta})$), which is used as a regressor in the probit model of the second stage (i.e. equation 3.5). According to (Wooldridge, 2010, p.814), such a two step approach can be used to test for sample selection. The procedure can also be employed to address selection bias (See Cameron and Trivedi, 2005, p. 550).

But before estimating the selection model, it is essential to know the variables that affect selection. Using a stepwise regression approach, I find that the three variables that are significant determinants of the probability of taking a loan are age, whether the individual has an immediate family member living abroad, and the borrowers previous loan history, i.e. whether the borrower has in the past taken a loan from a Bank or not. Given that having a family member living abroad is found to be irrelevant in explaining the probability of default but relevant for explaining the likelihood of taking a loan, it is the variable used for the exclusion restrictions, which has to be satisfied for the method to be valid. The motivation for using this

TABLE 3.7: First Stage Regression Output: Selection Model

	Reloan	AME
Age	0.028*** (0.006)	0.006*** (0.001)
Fabrd	-0.571*** (0.050)	-0.133*** (0.013)
Bank	1.164** (0.530)	0.142*** (0.019)
_cons	0.166 (0.239)	
Pseudo R2	0.147	
N	513	513

*** 99% significance; ** 95% significance; *90% significance.

Note: Reported in parenthesis are the robust standard errors. Reloan is the indicator variable of whether a participant has already received a group loan or not; thus, it is 1 for participants who have received a group and 0 otherwise. Thus, reported under the Reloan column are the the probit estimates of the probability of taking a loan; AME = Average Marginal Effects. Shown on the last two rows is, respectively, the Pseudo R square for the estimated model and the number of observations in the sample. Bank is an indicator variable of whether the participant has once taken a loan from a formal bank, it is 1 if the participant has done so and 0 otherwise. Description of the remaining variables are reported in table 3.3.

variable for the exclusion restriction is supported by studies on international remittances and household behaviour in developing countries (like Gambia's neighbors Senegal). For instance, [Mbaye \(2015\)](#) finds that remittances has a positive impact on the likelihood of taking a loan in Senegal, and [Randazzo and Piracha \(2013\)](#) did not find evidence that international remittances increases household expenditure on house and land including loan repayment. Hence, is possible for the family member living abroad variable to be a determinant of the likelihood to take a loan and not the likelihood to repay it.

Therefore, the first stage regression results of the sample selection model are reported in Table 3.7. The first column of the table reports the estimate of the probability of taking a loan, and the associated AMEs are reported in the second column. All the three variables have the expected sign on the likelihood of taking a loan. Specifically, an additional age increases the probability of taking a loan by 0.6 percent and is statistically significant. The probability of taking a loan is 13 percent lower for borrowers with a family member living abroad than borrowers without

TABLE 3.8: Second Stage Regression: Main Model

Dependent Variable: Individual Default		
	Logit	Heckit
ExTra _{a1}	-0.054*** (0.044)	-0.111*** (0.027)
AgRea _{a1}	-0.228** (0.081)	-0.191*** (0.040)
ConSci _{a1}	0.004 (0.082)	-0.030 (0.042)
NeuTis _{a1}	-0.173** (0.075)	-0.160*** (0.030)
Open _{a1}	-0.080* (0.044)	-0.095* (0.026)
Socindex	-0.102*** (0.019)	-0.053*** (0.011)
Gssindex	-0.320*** (0.051)	-0.060*** (0.015)
Educa	0.428*** (0.071)	0.270*** (0.072)
Ownbuz	-0.063** (0.221)	-0.090** (0.085)
Age	-0.014*** (0.001)	-0.010*** (0.003)
Married	0.037 (0.200)	-0.068 (0.092)
Fabrd	-0.175 (0.091)	-0.116 (0.116)
Grotyp (SG)	0.810** (0.281)	0.455*** (0.112)
Athrho		-0.024 (5.115)
Insigma		-0.824*** (0.044)
F stats	23.36	20.53
N	419	504

*** 99% significance; ** 95% significance; *90% significance. Reported in parenthesis are the jackknife standard error that corrects for clustering at the group level.

Note: Logit= logistic regression results from specification III of table 3.6, which is estimate on just sub-population of participants who have once taken a group loan; Heckit = Results from the second stage regression using the Heckman selection model; Athrho = Inverse hyperbolic tangent of ρ , which is estimated instead of ρ to ensure that ρ is within (-1,-1). $\ln\sigma$ = Natural log of σ ; σ^2 is the variance of the errors of the selection model and the main model. $F - stats$ = F statistics. All the personality trait variables are standardized.

a family member living abroad, which is also highly significant; thus, this result differs from what Mbaye (2015) finds for his study in Senegal. However, this effect is plausible in the sense that access to international remittance makes additional means of finance available to an individual, hence, it can decrease the individual's demand for loans. As expected, having previously taking a formal loan raises the probability of requesting for a group loan by about 14 percent and is statistically significant. The second stage results are reported in Table 3.8. Also reported in the table is the regression results from specification III of the logistic model (i.e. derived from the last column of Table 3.5). As the primary goal of the exercise here is to test for sample selection in the data, I focus the interpretation of the results on just this. The results indicate a ρ (computed from athrho reported in Table 3.8) of about 0.017, which means that the correlation between the errors in the selection model and the main model is 0.017, and σ (computed from $\text{ln}\sigma$ in the same table) of about 0.44. Thus, $\lambda=0.007$, which implies positive selection; that is, unobserved factors that make selection more likely also increase the likelihood of not repaying a loan. To test whether ρ is statistically different from zero, we use a standard Wald test. The Wald test on ρ reveals a p-value of 0.873, which implies that no evidence exist to conclude that it is not different from zero; therefore, no selection correction is required. Furthermore, the magnitude of the estimates of the coefficients in the two models do not differ hugely from each other. Thus, estimating the default probability on just the sub-population of participants who received their first loan does not seem to jeopardize the findings.

3.7 Conclusion

In analyzing the performance of microcredit programs, it is intuitively apparent that two significant factors are paramount; cognitive and non-cognitive factors of the borrowers. However, much of the focus in the group lending literature has been on studying the impact of cognitive traits of borrowers on their repayment behaviour. Although there has been a surge of interest to understand how non-cognitive traits affect the behaviour of an economic agents, not many studies exist that focus on the impact of these traits on behaviour in credit markets; in particular, the microcredit

markets in developing countries. This study aimed to fill this gap. Using a data collected from an NGO group-based microcredit program targeting only women in Gambia, I find evidence that personality traits measured from the Five-Factor model do affect the behaviour of borrowers in joint liability lending programs. In this regard, the results differ from KMR, who found no reliable evidence that these traits affect behaviour. Therefore, the evidence suggests that adverse selection problems in microcredit cannot be ignored; especially, in the context of credit markets in developing countries.

Among the five domains measuring personality traits of the BFI, I find evidence that all factors, except Conscientiousness, do influence default behaviour. The evidence that traits like Agreeableness significantly affect repayment behaviour in group-based lending schemes is captivating as cooperation among members of a group, concerning monitoring each other, is among the core factors that explain the success of group-based lending. Thus, if microcredit providers could sort borrowers according to these traits, they could improve the performance of their schemes. Furthermore, this means incorporating tools that reveal borrowers non-cognitive traits in microcredit programs will lead to better performance. Aside from personality traits, I also find evidence that social capital matters for repayment behaviour. Also, other cognitive traits such as age, business ownership, and education also matter.

The study has (undoubtedly) its limitations. The first limitation is that I do not have a structural model from where I can infer with much certainty that the relationship between personality traits and the default behaviour is a causal one, which also affects the external validity of the results. Therefore, any further research in this direction could help in the better understanding of the impact of personality traits on the behaviour of microcredit borrowers. The second limitation is that I rely on a very restrictive assumption to argue for the independence of the personality traits and social capital variables; specifically, I use evidence on the stability of traits from previous research to motivate that these variables can be assumed to be exogenous in my context. The third limitation is that the reliability indices of some of the elements of the BFI are not that high when compared to previous studies - mostly in the psychology literature. I think this could be because I am using a brief instrument relative to these studies; although the BFI instrument used in this study is not that

brief when compared to many studies in economics that use the BFI. The fourth limitation is that the study is based on just women borrowers as they were the targets of the lending institution; hence, I could not look at whether gender differences in personality traits matters for repayment behaviour. I leave these issues for future research.

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Appendices

Appendix C

Additional Tables and Figures and BFI Questionnaire

C.1 Table

TABLE C.1: Determinant of Joining a Group

Dependent Variable: Member of Groups [†]	
	logit
NeuTis _a 1	0.218 (0.127)
Open _a 1	0.019 (0.129)
ConSci _a 1	0.213 (0.136)
AgRea _a 1	-0.253 (0.149)
ExTra _a 1	-0.321* (0.119)
Controls added [‡]	yes
Pseudo R^2	0.13
LR <i>chi</i> ²	90.44
<i>N</i>	500

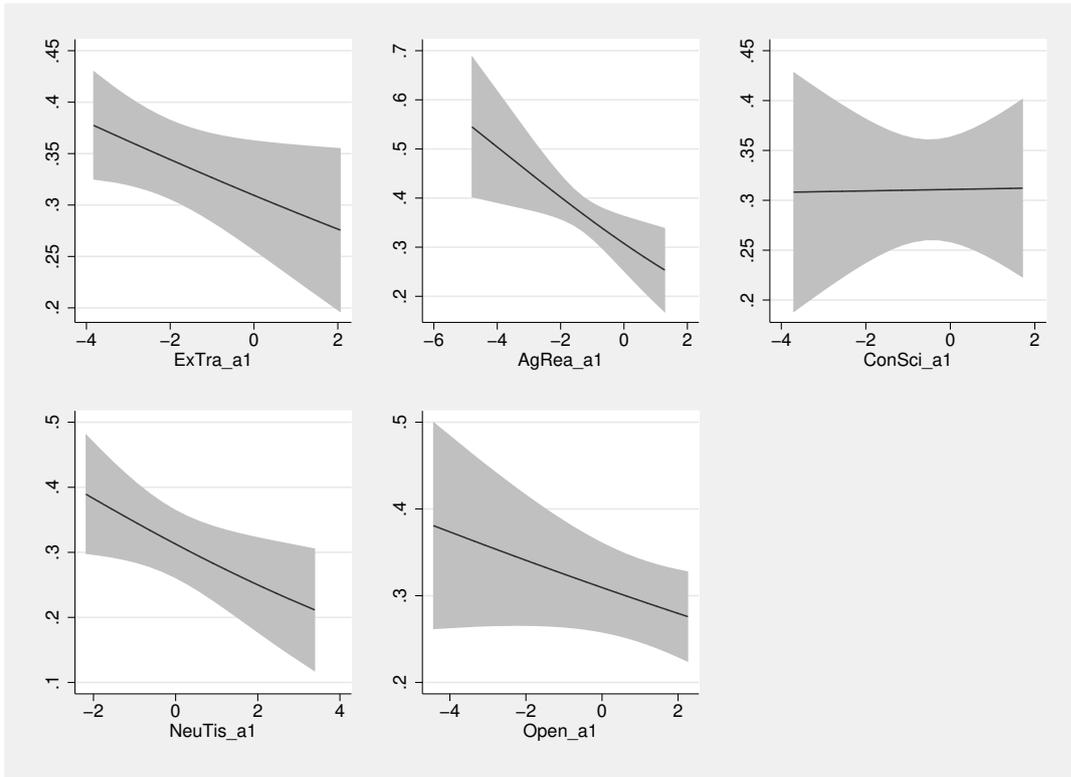
*90% significance.

[†] Membership in the following three groups is considered: Religion, political, and other loan groups.

[‡] The control variables included were age marital status education and ethnicity.

C.2 Figures

FIGURE C.1: Marginal Effects of Critical Core Variables (Logit of Model III)



The shaded areas on the graphs are the 95% confidence bands

FIGURE C.2: Marginal Effects - Social Capital Variables (Logit of Model III)

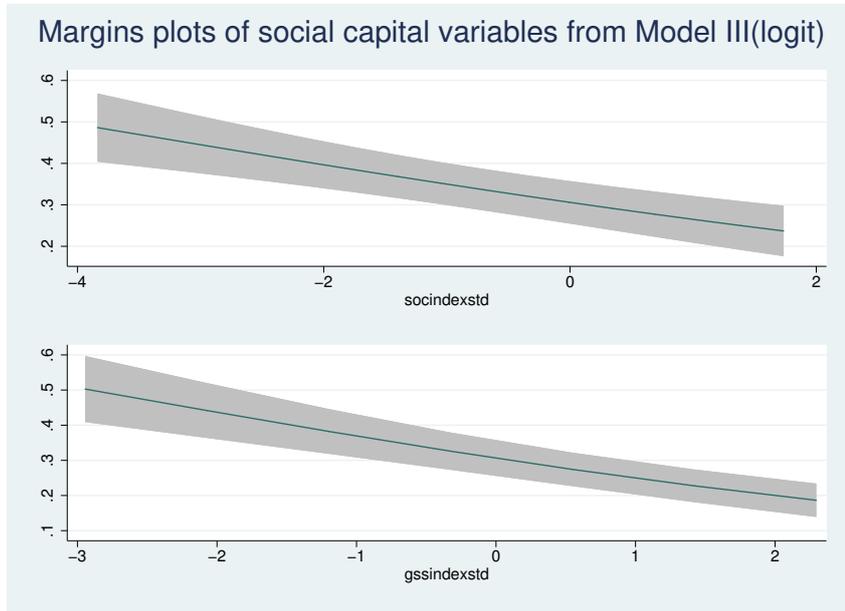
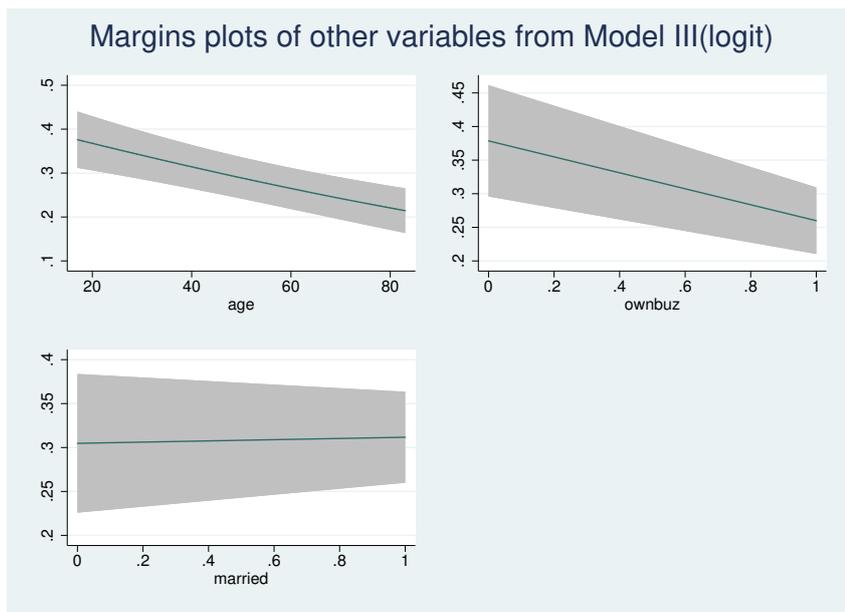


FIGURE C.3: Marginal Effects - Continuous Variables (Logit of Model III)



C.3 Questionnaire

C.3.1 BFI Questionnaire

Extraversion

1. I see myself as someone who is a talkative
2. I am someone who is full of energy
3. I see myself as someone that generates a lot of enthusiasm
4. I am someone who tends to be quiet (R)
5. I see myself as a person with an assertive personality
6. I am someone who is outgoing and sociable

Agreeableness

7. I see myself as a person who starts quarrel with others (R)
8. I see myself as someone who has a forgiving nature
9. I am someone who is generally trusting
10. I am someone who is considerate and kind to almost everyone
11. I consider myself as someone that is sometimes rude to others (R)
12. I am someone who likes to cooperate with others

Conscientiousness

13. I see myself as someone who does a thorough job
14. I see myself as someone who can be somewhat careless (R)
15. I am a person who is a reliable worker
16. I see myself as a person who tends to be disorganized (R)
17. I am someone who tends to be lazy (R)
18. I am someone who is perseveres until the task is finished
19. I am someone who does things efficiently
20. I am someone who make plans and follows through with them

Neuroticism

21. I see myself as someone depressed
22. I see myself as someone that is relaxed and handles stress well (R)
23. I see myself as a person who can be tense
24. I can be someone who is moody
25. I am someone who remains calm even intense situations (R)

Openness to Experience

26. I see myself as someone original and come with new ideas
27. I consider myself as someone who has an active imagination
28. I am a person who is inventive
29. I am someone who prefers work that is is routine (R)
30. I am someone who is sophisticated in art, music, or literature

C.3.2 Bonding Social Capital Questionnaire

For the following 5 questions please describe to what extent does each of the statements apply to you. Note that a one means it does not apply to you and 5 means it very strongly apply to you.

1. I live in a close-knit neighborhood

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)

2. People in my neighbourhood are generally willing to help their neighbours

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)

3. In my neighbourhood, people don't generally like each other

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)

4. People in my neighbourhood don't share the same value

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)

5. People in my Neighborhood can be trusted

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)

C.3.3 Perception on Trust Questionnaire

1. Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?

- Most can be trusted
- Can't be too careful

2. Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?

- Would take advantage of you
- Would try to be fair

3. Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?

- Try to be helpful
- Just look out for themselves

Affirmation

I hereby affirm that I have completed my doctoral thesis entitled "Essays on Financial Inclusion, Food Security and Nutrition in Developing Countries" entirely on my own and unassisted, and that I have specially marked all of the quotes I have used from other authors as well as those passages in my work that are extremely close to the thoughts presented by other authors, and listed the sources in accordance with the regulations I have been given.

Banjul, February 4, 2019

Hamidou Jawara