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2018

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Abstract

The paper analyses the impact of using single, combinations and the range of three different formal financial services – savings, credit and payments – on the personal food security experience in rural areas across 88 low-and middle-income countries. It takes advantage of Global Findex database and Food Insecurity Experience Scale (FIES) – both included in the 2014-round of Gallup World Poll that collects data at individual-level and comparable worldwide. Our outcome variable of interest is the individual's probability of experiencing food insecurity related to difficulties in access to food and which we measure through FIES. Econometrically, we employ different matching techniques: entropy balancing, matching on propensity scores and fully interacting linear matching in order to assess the consistency of estimated impacts. The results indicate mixed food security effects depending on the type of service used. Use of savings accounts significantly decreases, use of credit significantly increases and use of formal payment services has no effect on the individual's probability of experiencing food insecurity. Our findings are consistent with the view that the specific features rather than the range of services offered by formal financial sector is determinative in the final food security experience, especially when they can be assigned to positive income effects.

September 2017

Keywords: financial inclusion, experience-based food insecurity scale, rural populations, low-and middle-income countries, impact, entropy balancing.

JEL Classification: D11, D14, G21, O17, Q18, R51.

Introduction

The number of people that are excluded or underserved by the formal financial sector concentrates in rural areas of low-and middle-income countries, where there is also a coincidence in the concentration of poverty (Chen and Ravallion, 2008; Chen and Ravallion, 2012; Demirguc-Kunt *et al.*, 2015). The livelihoods of rural families in these countries are diversified in a myriad of agricultural and non-agricultural economic activities (Ellis, 1998 and 2000; Barrett et al., 2001). Although for many rural households agriculture is not the main source of income partially because it is characterized by a high degree of covariate risks and seasonal income fluctuations, it remains a key economic sector providing an important source of income and production for household consumption and the market (Davis *et al.* 2010; FAO, 2016a).

Given the rural context, i.e. high transaction costs in areas with low population densities and the complexity of assessing the risk profile of rural clients, it has been difficult for the formal financial institutions with their current business model to sustainably offer their services to rural populations. As a result, rural financial markets remain fragmented where several financial service providers coexist and those informal ones tend to dominate given the informational advantages they possess (Adams and Fitchett, 1992; Conning and Udry, 2007; FAO, 2016a).

The establishment of Maya Declaration in 2011 has been an important progress that made financial inclusion for all, and especially for the poor and vulnerable population, a policy priority in many developing countries. The 2030 Agenda for Sustainable Development defines financial inclusion as “secure and equal access to financial services” and recognizes it as “a powerful enabler” to end hunger, achieve food security and improve nutrition, and promote sustainable development (UNSGSA, 2016). Food security was formally recognized as a human right more than half a century earlier by the United Nations in the Universal Declaration of Human Rights (1948). The Rome Declaration on World Food Security (1996) provides a complex but generally recognized definition: “food security exists when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life”. This physical and economic access to food is what we believe to be judged by individuals themselves depending on their possibility to use adequate financial services and how this can affect their income and food consumption.

Financial services represent tools that can potentially help manage the household income available for investments and consumption. How efficiently this can be achieved might depend on their specific features as well as on the adequate suite of financial services available to the household. This could further bring positive results in terms of food security experience of household members as they would feel more confident about their economic resources to access food when needed. However, using financial services may also imply significant costs to the household that might be hard to sustain and could ultimately lead to a deterioration of its food security situation. As common examples in the literature show, household members keep savings in case of a livelihood threatening shock at the expense of any profitable investments or turn to a very costly emergency loan solution when the shock already occurs (Demirguc-Kunt *et al.* 2017). Therefore, analytical frameworks developed suggest thatthe impact of financial services on food security is theoretically ambiguous and determining such impact is an empirical exercise, which we explore in this paper.

A vast literature explores the role and impact of financial markets in overall socio-economic development and supports the recognition of financial inclusion as an important policy priority for low- and middle-income countries. At a macro level, the cross-country evidence suggests that as the financial system develops offering a wide set of services, with greater outreach and depth, it reduces poverty and inequality and increases economic growth (Demetriades and Hussein, 1996; Levine, 1997 and 2005; Jalilian and Kirkpatrick, 2002 and 2005; Honohan, 2004; Beck *et al.*, 2004, 2007; Sarma and Pais, 2011). At a micro-level, the framework of household's risk-coping and risk-management strategies[1] is used to explain how financial services like credit, payments, insurance or savings help households smooth consumption and make better investment decisions (Townsend, 1994 and 1995; Rosenzweig and Wolpin, 1993; Udry, 1990 and 1994; Dercon, 1996; Dercon and Krishnan, 1996; Fafchamps *et al.*, 1998; Karlan *et al.*, 2014). The empirical evidence on the topic has mostly focused on assessing specific financial products and small-scale "poor-oriented" (both governmental and non-governmental) initiatives in various socio-economic contexts and regions and targeted different indicators of human well-being.[2] It did not, however, bring a straightforward evidence on the positive effects of financial inclusion on key aspects of human well-being, including the food security one.

The role of financial inclusion in household's food security in particular has been examined only indirectly. Researchers have been equally employing household consumption, food expenditures, calorie intake and anthropometrics as a proxy to measure the food security outcome.[3] This is likely to be, in part, due to the difficulty of defining such a complex variable as food security for the purpose of conducting empirical analysis. On the contrary, the Food Insecurity Experience Scale (FIES) indicator used in this study aims at measuring the fundamental nature of food insecurity. Webb et al. (2006) and Pérez-Escamilla and Segall-Corrêa (2008) argue that personal experience of food deprivation reflects the real condition of food security more accurately than any of the derived measurements that in themselves may be the cause or consequence of food insecurity, and their ability to approximate food security depends on a particular context. In addition, the new approach that FIES represents in measuring food security fills a gap in the efforts to compare the concept of food security across countries. In terms of policy implications, use of such indicator might be particularly relevant in order to make sure that the given policy solution is effectively addressing the real condition of food insecurity.

In contrast to previous research, this paper provides a cross-country evidence on the impact of *any* formal financial product – namely savings, credit and payments, used alone and in combination – on the individual's probability of experiencing food insecurity. We examine the overall situation of rural areas of low-and middle-income countries where the financially excluded or underserved and the food insecure part of population concentrates. We limit our focus to formal financial services due to the difficulty to assess the accuracy and reliability of information on the use of informal financial services.

[1] Alderman and Paxson (1992), Dercon (2002).

[2] A snapshot of such studies include Diagne and Zeller, 2001; Khandker, 2005; Karlan and Zinman, 2011; Crépon et al., 2011; Roodman and Morduch, 2014; Banerjee et al., 2015; Demirguc-Kunt et al., 2017.

[3] To our best knowledge, such studies (all focusing on very specific contexts) include Schrieder (1996), Diagne and Zeller (2001), Deininger and Liu (2009) Ksoll et al. (2015) and Islam et al. (2016).

To study the relationship between the use of financial services and food security at the individual level worldwide, we rely on cross-sectional data. The data were collected during Gallup Worldwide Research survey carried out in 2014 in more than 150 countries around the world. The survey included two additional question modules key to our analysis. The first module interrogates on the access and use of several financial services, their type and origin, to create Global Findex database (World Bank, 2014). The second module collects responded items for the purpose of constructing the Food Insecurity Experience Scale (FIES) indicator (FAO, 2014). Considering the problem of sample selection bias due to the non-experimental design of our dataset, we employ different matching methods – entropy balancing, propensity score matching and fully interacting linear matching – to estimate the impact of using different financial services on the probability of experiencing food insecurity.

We find that use of formal saving services is the only one of the three tested financial products that significantly reduces the probability of experiencing food insecurity among individuals living in rural areas of low-and middle-income countries. The effect is negligible for payment services and significantly adverse for credit. Such results imply that those individuals that decide to save at a formal financial institution to manage potential risks are able to accumulate and access extra money when needed, and thus are not likely to worry about the resources needed to obtain food. Yet, taking a credit to undertake an important investment decision or manage household liquidity when own financial resources are insufficient implies a repayment commitment that may put enough burden on income and consumption to worsen the personal experience of securing enough food, as measured by FIES. Payment services are commonly used as the means for all sorts of optimal or non-optimal transactions, indifferently to income level, and thus are unlikely to directly influence the food security experience.

The paper is organized into four sections. In Section 1, we present the impact estimation methodology, in Section 2 we describe the data and variables used in the analysis, in Section 3 we present our results and we further discuss them and conclude in Section 5.

1. Estimation strategy

We approach the question as impact evaluation problem where the use of various financial services is our treatment. This approach requires constructing a counterfactual, i.e. the outcome for those being treated had they not been treated. With regard to the non-experimental nature of our data, our counterfactual is missing since we can only observe the difference in outcomes between those who used formal financial services and those who did not – the problem known as "selection bias" (Heckman and Hotz, 1989). Most of the existing non-experimental methods tackle the issue building on the assumption of "selection-on-observables", i.e. conditional on observable characteristics the difference between treated and non-treated is due to the treatment (Heckman and Robb, 1985). If this assumption holds, then treated observations can be matched with those non-treated that are sufficiently comparable according to specific criteria.

In this study, the units of analysis are individuals. We define with $Y(1)$ and $Y(0)$– respectively - the outcome of the users and non-users of a given financial service and with T a binary variable being equal to 1 whether a unit was exposed to the treatment and 0 otherwise. Our measure of interest is the so-called Average Treatment Effect on the Treated (ATT), which can be expressed as follow:

$$\tau_{ATT} = E[Y(1) - Y(0)|T = 1) = E[Y(1)|T = 1] - E[Y(0)|T = 1]\,, \tag{1}$$

The ATT measures the difference between the expected food security for those individuals that do not use formal financial services, and expected food security for those who actually have access to financial services. While $E[Y(1)|T = 1]$ is available, the outcome of the users if they had not received the treatment, $E[Y(0)|T = 1]$, i.e. our counterfactual, cannot be observed but can be approximated. This identification is possible if the conditional independence assumption (CIA) holds, which implies that once we control for those observable characteristics the decision of using or not-using formal financial services can be considered random (Dehejia and Wahba, 1999). The estimate of the ATT based on the assumption of independence conditional on covariates can be defined as:

$$\tau_{ATT}(x) = E[Y(1)|T = 1, X = x] - E[Y(0)|T = 0, X = x]\,, \tag{2}$$

where X is a vector of exogenous covariates that influence both the outcome and the treatment but are unaffected by the treatment (Imbens, 2004) – by the use of formal financial services in our case. The estimation problem in equation (2) can be resolved through matching the treated units with untreated units that are as similar as possible in pre-treatment characteristics. Propensity Score Matching (PSM) was introduced by Rosenbaum and Rubin (1983) to this purpose, and became the most commonly used matching technique for non-experimental impact evaluation. The method gained popularity for its property to address sample selection bias due to observable differences between the treatment and comparison groups and reduce this information into one parameter, propensity score, which is conditional probability of being treated based on the observable covariates.[4] In the first step, the propensity scores are estimated through a logistic regression and – in the second step – used for matching treated and control units to calculate the ATT. With respect to the CIA, the distribution of covariates between treatment and control group needs to be balanced after matching on propensity scores – a balancing property of propensity scores (Rosenbaum and Rubin, 1983). This condition involves in searching for the best specification of model used to estimate propensity scores to achieve satisfying balanced covariate distribution; and which often results in improving balance on some covariates at the cost of that of another (Ho *et al.*, 2007; Hainmueller 2012; Watson and Elliot, 2016).

To overcome practical limitations of the precedent method in achieving balancing property, we employ the so-called Entropy Balancing, a pre-processing method recently proposed by Hainmueller (2012), as our principal method of analysis. The method has already gained some popularity in applied economics (Marcus, 2013; Neuenkirch and Neumeier, 2016) mainly because of its easy implementation. The purpose of this technique is creating balanced weights for treated and control units which can be subsequently employed for estimating the ATT through regression analysis. The method requires two-step procedure. In a first step, the reweighting scheme assigns weights to our control observations not using any financial service such that the pre-specified moments (i.e. means, variances and skewness) of their observable characteristics match with those of the treated, i.e. using any financial service, while remaining as close as possible to uniform base weights. Since after reweighting the treatment becomes moments-independent of all control covariates (which also

[4] For further discussion on its advantages see, for example, Rosenbaum and Rubin, (1983); Heckman et al. (1997) and Dehejia and Wahba (2002).

reduces the unobserved variance in outcome), the counterfactual mean in equation (1) can be estimated as:

$$E\left[\widehat{Y}(0)|T=1\right]=\frac{\sum_{\{i|T=0\}}Y_i\omega_i}{\sum_{\{i|T=0\}}\omega_i}, \tag{3}$$

Where ω_i is a weight assigned to each control unit based on a reweighting scheme that minimizes the following entropy distance metric:

$$\min_{\omega_i} H(\omega)=\sum_{\{i|T=0\}}\omega_i \log(\frac{\omega_i}{q_i}) \tag{4}$$

Subject to balance and normalizing constraints

$$\sum_{\{i|T=0\}}\omega_i\, c_{ri}(X_i)=m_r \tag{5}$$

$$\text{with} \qquad r\in 1,\dots,R\,; \qquad \sum_{\{i|T=0\}}\omega_i=1 \text{ and } \qquad \omega_i\geq 0 \text{ for all } i \text{ such that } T=0, \tag{6}$$

where $q_i = 1/n_0$ is a base weight when we have n_0 control units and $c_{ri}(X_i) = m_r$ describes a set of R balance constraints imposed on the covariate moments of the reweighted control group (Hainmueller, 2012). In our study, we set R equal to 3 which means that the reweighting scheme needs to adjust covariate means, variances and skewness of our control sample.[5]

In the second step, we estimate the functional relationship between our treatment and outcome variable on the entropy balanced reweighted sample by means of Ordinary Least Squares (OLS) and Generalized Linear Model (GLM). Our outcome, the food insecurity experience, is regressed on the treatment variable determining whether an individual used any financial service or not and on the set of control covariates – the same we used in the reweighting step. In addition, we include country-fixed effects to account for potential unobserved heterogeneity across countries. Our dependent variable, i.e. the experience of food insecurity, has a probabilistic distribution bounded by 0 and 1. The OLS predicts this probability as a normally distributed variable with values going below 0 and above 1 and assumes linearity of the relationship. Alternatively, we apply the so-called fractional logit model as proposed by Papke and Wooldridge (1996) and which can be estimated by means of the Generalized Linear Model (GLM) with logistic binomial distribution. This allows for boundary observations being generated by a different process than those being in the middle of distribution (Baum, 2008). This method is more appropriate for the case of dependent variable being a proportion or percentage with many values equal or close to 0 and 1.

The key advantage of entropy balancing, as compared to traditional matching techniques, is the ease with which the balancing property of covariates is achieved (Hainmueller, 2012, 2013). Balance constraints imposed directly by researcher to estimate entropy weights ensure that the reweighted groups match exactly on the specified moments. Secondly, matching methods assign binary weights to the observations in the control group – one if they match and zero otherwise – and discards those observations with zero weights. Instead, entropy balancing assigns positive weights to all the units in the control group, allowing to exploit the full sample. Third, the estimated weights are maintained as

[5] We choose to adjust our control sample up to the third covariate moment in order to ensure perfect balance between our treated and control samples in terms of identical distribution of their covariates. However, our results show to be robust to different specifications of constraints imposed on covariate moments of our control sample.

close as possible to the base weights which prevents loss of information for the subsequent analysis. Lastly, the weights obtained from entropy balancing can be applied as survey weights in almost any standard estimator for the subsequent estimation of treatment effects. In comparison with simple regression analysis without entropy balancing in the pre-processing stage, the estimates based on entropy balanced sample are less likely to suffer from multicollinearity since entropy balancing orthogonalizes the treatment variable with respect to the covariates that are included in the reweighting process (Hanmueller, 2012).

For the sake of completeness, we report also the Propensity Score Matching (PSM) and Fully Interacting Linear Matching (FILM) estimates as robustness checks. The PSM allows us to control for the presence of unobserved heterogeneity through the so-called Rosenbaum bounds test (Rosenbaum, 2002). The Rosenbaum bounds test measures the amount of unobserved heterogeneity we have to introduce in our model to challenge its results, i.e. the presence of unobserved covariates that simultaneously affect our treatment, the use of financial services, and our outcome, the food insecurity experience. The FILM allows for heterogeneous effects of the treatment by adding interaction terms between covariates and treatment variable to the linear model (Sianesi, 2010). In other words, the effect of using any financial service may vary according to each observable characteristic and one can actually test for the presence of such heterogeneous effects.

2. Data and variables description

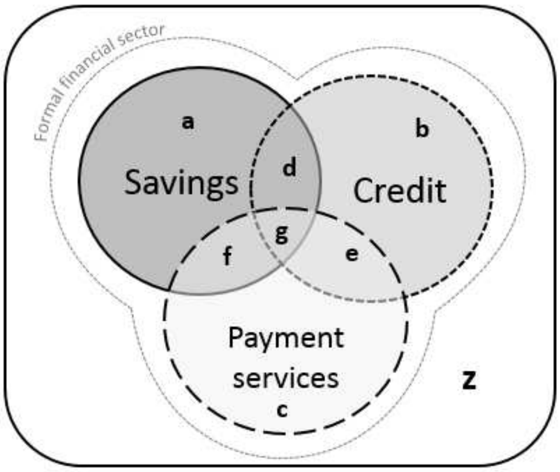
We use cross-sectional data from Gallup Worldwide Research survey collected in 2014 by Gallup® World Poll in more than 150 countries over the world. Data were collected at individual level using randomly selected, nationally representative samples of the resident population aged 15 and more. A typical Gallup's country representative sample includes 1,000 individuals selected through three-stage sample identification approach (Gallup, 2015). The survey has been conducted every four years but the 2014 round is the only one that includes both financial inclusion and food insecurity modules. Questions in the first module relate the state of financial inclusion in the world for the purpose of Global Findex database (World Bank, 2014). The second module collects information needed to construct the Food Insecurity Experience Scale (FIES) indicator (FAO, 2014). In our analysis, we used a sub-sample of the available data focusing only on the rural residents in countries classified by World Bank as low-income, lower middle-income and upper middle-income. Our sample consists of 58,295 observations from 88 countries (23 low-income and 65 middle-income).

Treatment variables. As already mentioned, the primary interest of this paper is the impact of formal financial services on food security. By "formal" we refer to those services provided by a bank or another type of financial institution, such as credit union, cooperative, microfinance institution as well as mobile money providers. For the sake of completeness, we create a series of treatment variables based on the use (combined or not) of savings, credit and payment services[6] in the past 12 months and run

[6] Under the definition of payment services we include inflows of wage payments, government transfers agricultural payments and domestic remittances; and outflows of utility bills, school fees and domestic remittances. The Global Findex survey does not cover international remittances justifying as "while these remittances are economically important for some countries, the share of adults in developing economies who reported sending or receiving domestic remittances is on average three to four times the share who reported sending or receiving international remittances" (Gallup World Poll, 2014).

our analysis on each one of the different options always against the same control group. We build three groups of binary variables to be used as treatment (T) in the econometric exercise. With the first group, we aim at establishing the overall impact of using any type of formal financial service on food security, focusing on the effect of the degree of financial inclusion and not on the effect of specific services. To do that, we create three binary variables. The first is equal to one if the individual has used one formal financial service, irrespectively of the type. Looking at Figure 1, it includes those who saved (area a), borrowed (area b), or used payment services (area c) for a total of 12,968 individuals. The second is equal to one if the individual has used two financial services at the same time, regardless of their possible combinations. It includes area d, e and f in Figure 1 for a total of 5,420 individuals. The third is equal to one if the individual has used all three financial services at the same time, which is represented by area g with 1,216 observations. It is important to note that the three variables are mutually exclusive because who is treated in the first case cannot be treated in the second neither the third one. In the second group, we test the impact of the services one by one in the way that our treatment variables restrict to the individuals that have used only one of the three services. We create: 1) a binary variable equal to one if the individual has only saved (area a with 2,318 observations); 2) a binary variable equal to one if the individual has only accessed to credit (area b with 2,384 observations); 3) a binary variable equal to one if the individual has only used payment services (area c with 8,266 observations). The treated groups are again mutually exclusive, allowing us to isolate the impact of the single service. Finally, we examine effect of the interactions among financial services by considering the impact of their specific combinations. More specifically, we create: 1) a binary variable equal to one if the individual has saved and borrowed at the same time (area d with 658 observations); 2) a binary variable equal to one if the individual has saved and used payment services at the same time (area f with 3,191 observations); 3) a binary variable equal to one if the individual has borrowed and used payment services at the same time (area e with 1,571 observations). For the sake of consistency and to facilitate the comparison between services, we always use the same control group for the different financial services, i.e. the subset of zeros in our binary variables. In particular, we use as control group the individuals that have not used any formal financial service during the period of the survey, but we do not exclude the possibility of using informal sources. This is represented by the units of observation in area z of Figure 1, which counts 38,690 individuals.

Figure 1: Graphic representation of treatment sub-groups and definition of treatment variables



Treatment sub-group	Variable definition	Variable name	Nb. of observations
a + b + c	Used only one formal financial service in past 12 months	formal_1	12,968
d + e + f	Used two formal financial services in past 12 months	formal_2	5,420
g	Used three formal financial services in past 12 months	formal_3	1,216
a	Only saved formally	save_only	2,318
b	Only borrowed formally	borr_only	2,384
c	Only used formal payments services	pay_only	8,266
d	Saved and borrowed formally	save_borr	658
f	Used formal sources only for savings and payments	save_pay	3,191
e	Used formal sources only for borrowing and payments	borr_pay	1,571
z	*Did not use any formal financial service in past 12 months*	*control*	*38,690*

Number of observations are for the sample restricted to rural population.

Explanatory variables. From an empirical point of view, the matching procedure imposes us to control for observed characteristics that are likely to influence selection to the treatment or affect our outcome variable on food insecurity; but are exogenous to the treatment, i.e. measured before treatment or are fixed over time. Considering that our dataset is a single cross-section and we cannot use pre-treatment variables, we are forced to use only those covariates which are not affected by time or are clearly exogenous. Taking these limitations into consideration, we chose a set of individual-level demographic and socio-economic characteristics that are assumed to be time-invariant, such as age and its square, a set of dummies for gender, achieved level of education, marital status, and occupational status (employed or not). Income level can be understood as determining both the need for using financial services and the probability of experiencing food insecurity due to economic constrains. We control for individual's income in two ways: 1) through a continuous variable measuring household income per capita in PPP at constant dollar prices across countries; and 2) through four dummies of within-income quintiles measuring individual's relative income with respect to the country's income distribution. We also include a variable assessing the degree to which respondents are connected via electronic communications (Gallup's communications index) and dummy for currently owning a business. We assume that people having access to communication services are also more likely to use financial services, especially from mobile money providers, as compared to those without access. Likewise, people owning businesses are more likely to have needs for using various financial services. Some people are not using financial services simply because they cannot access them for various reasons. Those driven by socio-economic individual-side characteristics are already captured in our set of covariates. But we additionally include a dummy for currently having an account at a financial institution or mobile money provider since it is an important prerequisite of using formal financial services.[7] We also include a dummy to control for using informal services since both our

[7] Note that while having an account is often understood by literature as a "good" proxy of access, we avoid this interpretation as we suspect that some people might have access but freely chose not to open an account.

treatment nor our control excludes the option of using additional informal source, and thus omitting this information could bias the estimated treatment effect. We report descriptive statistics for our set of control variables included in the process of entropy balancing in Table 1 of Appendix. We additionally include country-fixed effects, but only in the regression analysis for the reason suggested by Neuenkirch and Neumeier (2016), to account for unobserved country-specific heterogeneity arising from, for instance, differences in development level of formal financial sector and other country-specific social and economic environment.

Outcome variable. To measure our outcome, i.e. food insecurity, we take advantage of the Food Insecurity Experience Scale (FIES) indicator, a global standard, experience-based scale metric of food insecurity. In its construction, it relies on self-reported food-related behaviours, such as having to compromise the quality and quantity of the food, associated with difficulties in accessing food due to resources constraints (Ballard *et al.*, 2014). The fundamental assumption behind the FIES is that the severity of the food insecurity can be analysed as a latent trait (FAO, 2014). The measurement approach builds on Item Response Theory assuming that a quantitative measure of an underlying, unobservable construct, i.e. a latent trait, can be inferred from a set of dichotomous variables obtained as the result of a test (Ballard *et al.* 2013). In this case, dichotomous variables are people's responses to eight questions regarding their access to adequate food during 12 months prior to the survey. Each question refers to a different situation and is associated with a level of severity according to the theoretical construct of food insecurity underlying the scale. The concept of severity-ordering of items, known as Rasch model (Rasch, 1960), allows for estimating the probability that each respondent belongs to each of a number of classes of food insecurity (food secure, moderately food insecure, severely food insecure). The fundamental assumptions behind the measurement model are that (i) a higher severity of food insecurity will increase the probability of reporting any of those experiences and that (ii) experiences can be meaningfully ranked in terms of severity (Ballard *et al.*, 2013).

At micro-level, the indicator is expressed as probability of belonging to a given class of severity with two possible thresholds: moderate-or-more and severe. Since measuring food insecurity through the higher threshold of severity leaves out information on the remaining part of food insecurity, we adopt the lower threshold as less narrow definition of food insecurity. Defined as probability, the variable takes any value in the interval between 0 and 1 excluding 1[8] and its distribution is concentrated in two peaks on the extreme sides of the histogram in Figure 1 of Appendix. This indicates that a large number of our observations have either near-zero probability or near-one probability of food insecurity at the severity level defined as *moderate-or-more*. We report descriptive statistics (sample means and standard deviation) of our outcome variable, probability of experiencing moderate-or-more food insecurity, across our different treatments and compared to the control group in Table 2 of Appendix.

[8] The individual-level estimated probability of food insecurity is never equal to 1 since the maximum conditional likelihood procedure cannot yield a probability estimate for extreme raw scores of 0 or 8. Respondents with raw score zero are assumed to be food secure, with no measurement error, while those with raw score 8 are assigned arbitrary raw scores between 7.1 and 7.8. (Nord, 2014)

3. Results

In this section we provide results from our main method of analysis – Entropy Balancing – and compare with results from alternative estimation methods: Propensity Score Matching (PSM) and Fully Interacting Linear Matching (FILM). Specifically, we present results in terms of the estimated treatment effects of using various financial services on the probability of belonging to the food insecurity class defined as moderate-or-more. The exact values of estimated treatment effects that are distributed between 0 and 1 are reported in tables. Given that our outcome variable is expressed as a continuous probability, in text we multiply the coefficients by 100 for easier interpretation.

Table 1 reports covariate means and variances in parentheses for the treated and control group after the first step of entropy balancing procedure. The last column shows the distribution of control group before entropy balancing. For all our treatment variables, covariate moments between the two groups – treated and control – become identical after this step, indicating that the procedure successfully balanced our sample. OLS and GLM (fractional logit model) results estimated in the second step of entropy balancing procedure are reported in Table 2 and Table 3 respectively.

In each of Table 2 and Table 3, we have nine estimated equations, columns (1) – (9), corresponding to nine different treatments defined in Figure 1 of the previous section. In the first rows are the estimated treatment effects on food insecurity outcome. We also report coefficients for control covariates used in the reweighting stage and inclusion of country-fixed dummies. The estimated standard errors are in parentheses and number of stars next to coefficients indicate their statistical significance. Although the coefficients slightly differ, the results are robust between OLS and GLM.

In the first group of treatment variables that measure the overall impact on individuals that use one, two or three financial products simultaneously (irrespective of the type of product), columns (1) – (3) of Table 2 and Table 3, the estimated effect is negative. However, its magnitude varies depending on number of services used. In case of using only one service irrespective of the type, the effect is insignificant, equal to -0.1 percent when estimated through OLS and equal to -0.4 percent when estimated through GLM. In case of using two services irrespective of the type, the effect becomes significant at the 1% confidence level, equal to -2.6 percent when estimated through OLS and -3.3 percent when estimated through GLM. When using all three observed services, the effect is slightly lower, -2.4 percent in case of OLS and -2.7 percent in case of GLM, and significant only at the 10 % confidence level. Based on these results, we can conclude that the food security effect does not increase continuously with increasing the number of formal financial services used, if we ignore the type of service. Hence, the type of financial service is likely to matter in determining the effect on food security.

Columns (4) – (6) in Table 2 and Table 3 aim at isolating the impact of each specific service by restricting to the individuals that have used only one of the three services. The use of saving services alone reduces probability of food insecurity experience by 4.4 percent and 5.5 percent, respectively. The use of credit increases this probability by 4.6 percent and 5.3 percent, respectively (which is by roughly the same amount as the use of saving services decreases it). The estimates are statistically significant at the 1% confidence level. The use of payment services has negligible, statistically insignificant effect – 0.1 percent and 0.3 percent, respectively. These results indicate that only saving services have a reducing effect on food insecurity experience, in the situation when only one financial service is used.

In Table 2 and Table 3, the last group of treatment variables, columns (7) – (9), aims at estimating the food insecurity effect for individuals that have combined two different formal financial services. The use of savings combined with credit decreases the food insecurity experience by 3.3 percent (significant at the 5% confidence level) and 2.6 percent (significant at the 10% confidence level), respectively. Savings combined with payment services decreases food insecurity experience by 5.3 percent and 6 percent point, respectively, significant at the 1% confidence level. Use of only credit and payment services increases the food insecurity by significant 2.6 percent and insignificant 0.5 percent, respectively. From these results, the interactions seem to be unlikely to produce additional food security effects beyond the one produced by each service individually. The positive food security effect of using formal financial services appears to be driven by savings and inhibited by credit, while indifferent in relation to payment services.

We additionally comment on estimated effects for the individual's characteristics, the control covariates reported in Table 2 and Table 3. The fact that the individual has an account at a financial institution or through a mobile money provider – which may be assumed as a condition for using the formal financial services – reduces his food insecurity experience. But his food insecurity experience increases if he uses informal financial services. These effects are statistically significant in the majority of our treatment specifications, however, with no pattern in their respective magnitudes relatively to effects of treatments. Regarding other individual's socio-economic characteristics, the probability of experiencing food insecurity increases on average (i) insignificantly for woman; (ii) significantly but nonlinearly with age; (iii) insignificantly in case of being unemployed or out of workforce; (iv) significantly with increasing proportion of children in the household and (v) the statistical significance vary considerably in case of losing a domestic partner. The probability of food insecurity experience, on average, decreases significantly with (i) achieved higher than primary level of education; (ii) belonging to higher than first income quintile; (iii) having access to communication services; and (iv) currently owning business. The effect of income per capita measured in PPP at constant dollar prices appears to be quite low – around 1 percent – and statistically insignificant.

Results from the two alternative methods – PSM and FILM – are also discussed briefly in this section. Logit estimations of propensity scores, i.e. probability of being treated given the covariates, are reported in Table 2 of Appendix. We include the same set of covariates that we used in the reweighting step of entropy balancing and country-level fixed effects in the model estimating propensity scores. We choose to match one treated observation with three control observations on their propensity scores within a caliper width set to 0.2 of the standard deviation of the logit of the propensity score. Such matching option empirically proved to be the best performing in terms of minimizing mean square errors (Austin, 2006 and 2011). For the purpose of balance check after matching on propensity scores, we report in columns (4) and (5) of Table 4 the pseudo-R2s as indicators of absolute bias before matching and after matching. After matching the pseudo-R2 decreases to nearly-zero indicating a sufficient absolute bias reduction. The critical values of gamma in column (6) of Table 4 indicating how much unobserved heterogeneity we have to introduce in our model to question our results range between the lowest value of 1.0 for use of credit only (row (v)) to the highest value of 1.6 for use of saving services together with payment services (row (viii)). Even if a specific Γ threshold – below which results should be questioned – does not exist, the reported values of gamma that are too close to one cannot exclude the presence of unobserved heterogeneity. This means that the strongly positive food insecurity effect of using formal credit could be statistically questioned by the presence of unobserved heterogeneity.

In case of FILM, for each of our treatment variables we regress our food insecurity outcome on treatment, set of observable covariates, country fixed-effects and their interaction terms, i.e. each of our treatment variables interacts with one of the observable covariates or country fixed effects. The estimated ATT and robust standard errors in parentheses are reported in column (9) of Table 4. In addition to FILM-estimated ATT, we report in columns (10) and (11) respectively of Table 4 the F-test statistics and related p-values to test the null hypothesis that the mean treatment effects are the same across covariates. For all our treatments, the F-test rejects null hypothesis of no heterogeneous effects, which indicates that the impact on food insecurity experience is nonlinear based on observable covariates.

The estimated treatment effects through PSM and FILM, our alternative estimation methods, are reported in columns (3) and (9) respectively in Table 4. Overall, the results are consistent between PSM and FILM, and lead to the same conclusion as that on results from entropy balancing with one exception: on the contrary to what we found when applied the method of entropy balancing, results from PSM and FILM indicate that use of three formal financial instruments – treatment in row (iii) of Table 4 – further reduces the food insecurity as compared to the use of two instruments – treatment in row (ii) of Table 4. We also notice that the largest variations in the estimated treatment effect across the three different matching methods are for treatment variable defined as using formal credit and payment services at the same time. For this treatment variable, the estimated effect on food security ranges from insignificant 0.5 percent to significant 3.3 percent increase in the probability of food insecurity across the three methods, although always remains positive. But they all confirm that the best performing combination is the use of formal saving services together with payment services. The related decrease in probability of experiencing food insecurity is between 4.7 and 6 percent. Use of formal credit alone appears as the worst performing of all possible treatments. It increases the probability of food insecurity experience by between 3.2 and 5.4 percent, approximately the same magnitude by which use of savings alone decreases it.

If we examined only the number of formal financial services used regardless of their type (our first three treatment variables) and if we examined them only through PSM and FILM (our alternative matching methods), we would probably conclude that food insecurity experience reduced with using higher number of formal financial services. In such sense, using one formal financial service would be better than none at all, two would be better than one, and three would be better than two. However when disaggregating by the type of service used, all our matching methods show that the effects become heterogeneous[9]. In particular, use of saving services is the only significantly reducing the food insecurity experience while use of formal payment services alone has insignificant close to zero effect and use of formal credit alone is significantly increasing the food insecurity experience. As soon as payment services are combined with saving services, the impact estimate on probability of experiencing food insecurity becomes significantly negative, moreover slightly higher than in case of using saving services only. When credit is combined with savings, the food insecurity effect becomes also negative, however lower than in case of using saving services alone. It could be concluded that the positive food security effect of using formal financial services is driven by savings and inhibited by credit, while little responding to payment services.

[9] It should be noted that entropy balancing method was able to detect the heterogeneous effects already from the aggregated variables for which the results indicated that the food security effect did not increase continuously with increasing the number of formal financial services used.

Table 1: Table reporting means of covariates for Treated and Control after entropy balancing procedure (first step)

Variable	formal_1		formal_2		formal_3		save_only		borr_only		pay_only		save_borr		save_pay		borr_pay		Control before reweighting
	Treat	Control	Treat	Control	Treat	Control	Treat	Control	Treat	Control	Treat	Control	Treat	Control	Treat	Control	Treat	Control	
inform	0.914	0.914	0.954	0.954	0.976	0.976	0.922	0.922	0.926	0.926	0.903	0.903	0.955	0.955	0.944	0.944	0.956	0.956	0.759
	(0.078)	(0.078)	(0.044)	(0.044)	(0.024)	(0.024)	(0.072)	(0.072)	(0.069)	(0.069)	(0.087)	(0.087)	(0.043)	(0.043)	(0.053)	(0.053)	(0.042)	(0.042)	(0.183)
account	0.754	0.754	0.955	0.955	0.992	0.992	0.808	0.808	0.385	0.385	0.833	0.833	0.902	0.902	0.977	0.977	0.917	0.917	0.138
	(0.186)	(0.186)	(0.043)	(0.043)	(0.008)	(0.008)	(0.155)	(0.155)	(0.237)	(0.237)	(0.139)	(0.139)	(0.089)	(0.089)	(0.023)	(0.023)	(0.076)	(0.076)	(0.119)
woman	0.516	0.516	0.471	0.471	0.446	0.446	0.459	0.459	0.517	0.517	0.481	0.481	0.509	0.509	0.434	0.434	0.451	0.451	0.526
	(0.250)	(0.250)	(0.249)	(0.249)	(0.247)	(0.247)	(0.248)	(0.248)	(0.250)	(0.250)	(0.250)	(0.250)	(0.250)	(0.250)	(0.246)	(0.246)	(0.248)	(0.248)	(0.249)
age	39	39	39	39	39	39	39	39	41	41	37	37	39	39	38	38	40	40	37
	(252)	(252)	(210)	(210)	(141)	(141)	(281)	(281)	(212)	(212)	(249)	(249)	(198)	(198)	(233)	(233)	(182)	(182)	(309)
age_sq	1,799	1,799	1,750	1,750	1,676	1,676	1,826	1,826	1,915	1,915	1,627	1,627	1,746	1,747	1,656	1,657	1,780	1,780	1,644
	2.05E+06	(2,048,128)	1.74E+06	(1,741,354)	1.07E+06	(1,067,901)	2.32E+06	(2,316,258)	1.69E+06	(1,686,108)	1.92E+06	(1,920,900)	1.68E+06	(1,682,233)	1.88E+06	(1,875,910)	1.43E+06	(1,433,850)	(2,429,908)
educ_23	0.616	0.616	0.754	0.754	0.801	0.801	0.534	0.534	0.463	0.463	0.592	0.591	0.513	0.513	0.736	0.736	0.702	0.702	0.359
	(0.237)	(0.237)	(0.186)	(0.186)	(0.159)	(0.160)	(0.249)	(0.249)	(0.249)	(0.249)	(0.242)	(0.242)	(0.250)	(0.250)	(0.194)	(0.194)	(0.209)	(0.209)	(0.230)
emp_stat_46	0.353	0.353	0.225	0.225	0.162	0.162	0.360	0.360	0.371	0.371	0.335	0.335	0.230	0.230	0.241	0.241	0.193	0.193	0.515
	(0.228)	(0.228)	(0.174)	(0.174)	(0.136)	(0.136)	(0.231)	(0.230)	(0.233)	(0.233)	(0.223)	(0.223)	(0.177)	(0.177)	(0.183)	(0.183)	(0.156)	(0.156)	(0.250)
wid_div	0.156	0.156	0.148	0.148	0.125	0.125	0.144	0.144	0.144	0.144	0.133	0.133	0.130	0.130	0.144	0.144	0.118	0.118	0.142
	(0.132)	(0.132)	(0.126)	(0.126)	(0.110)	(0.110)	(0.123)	(0.123)	(0.123)	(0.123)	(0.115)	(0.115)	(0.113)	(0.113)	(0.123)	(0.123)	(0.104)	(0.104)	(0.122)
child_ratio	0.808	0.808	0.821	0.821	0.792	0.792	0.673	0.673	0.651	0.651	0.647	0.647	0.642	0.642	0.692	0.692	0.657	0.657	0.591
	(0.911)	(0.911)	(0.859)	(0.859)	(0.800)	(0.800)	(0.646)	(0.646)	(0.480)	(0.480)	(0.609)	(0.609)	(0.386)	(0.386)	(0.691)	(0.691)	(0.463)	(0.463)	(0.609)
ln_percap_ income	6.934	6.934	7.408	7.408	7.688	7.690	6.915	6.915	6.817	6.817	6.792	6.792	6.925	6.926	7.317	7.318	7.319	7.320	6.072
	(3.856)	(3.856)	(2.944)	(2.945)	(2.274)	(2.274)	(3.287)	(3.288)	(2.375)	(2.375)	(4.466)	(4.467)	(2.664)	(2.664)	(3.119)	(3.119)	(3.048)	(3.048)	(4.496)
inc_q_2	0.173	0.173	0.118	0.118	0.082	0.082	0.162	0.162	0.244	0.244	0.194	0.194	0.167	0.167	0.124	0.124	0.172	0.173	0.241
	(0.143)	(0.143)	(0.104)	(0.104)	(0.075)	(0.075)	(0.136)	(0.136)	(0.184)	(0.184)	(0.156)	(0.156)	(0.139)	(0.139)	(0.108)	(0.108)	(0.143)	(0.143)	(0.183)
inc_q_3	0.199	0.199	0.175	0.175	0.156	0.156	0.209	0.209	0.226	0.227	0.206	0.206	0.276	0.277	0.181	0.181	0.220	0.220	0.205
	(0.160)	(0.160)	(0.144)	(0.144)	(0.132)	(0.132)	(0.165)	(0.165)	(0.175)	(0.175)	(0.163)	(0.163)	(0.200)	(0.200)	(0.148)	(0.148)	(0.172)	(0.172)	(0.163)
inc_q_4	0.220	0.220	0.231	0.231	0.225	0.225	0.236	0.236	0.174	0.174	0.217	0.217	0.202	0.202	0.250	0.250	0.207	0.207	0.172
	(0.172)	(0.172)	(0.177)	(0.177)	(0.174)	(0.174)	(0.180)	(0.180)	(0.143)	(0.144)	(0.170)	(0.170)	(0.161)	(0.161)	(0.188)	(0.188)	(0.164)	(0.164)	(0.143)
inc_q_5	0.254	0.254	0.383	0.383	0.484	0.484	0.258	0.258	0.133	0.133	0.203	0.203	0.209	0.209	0.360	0.360	0.236	0.236	0.125
	(0.189)	(0.189)	(0.236)	(0.236)	(0.250)	(0.250)	(0.191)	(0.191)	(0.116)	(0.116)	(0.162)	(0.162)	(0.165)	(0.165)	(0.230)	(0.230)	(0.180)	(0.180)	(0.109)
index_cm	58	58	64	64	68	68	56	56	55	55	61	61	56	56	65	65	67	67	43
	(884)	(884)	(908)	(908)	(840)	(840)	(876)	(876)	(858)	(858)	(938)	(938)	(832)	(832)	(923)	(923)	(905)	(905)	(996)
own_business	0.218	0.218	0.275	0.275	0.355	0.355	0.304	0.304	0.279	0.280	0.160	0.160	0.491	0.491	0.261	0.261	0.214	0.214	0.155
	(0.171)	(0.171)	(0.199)	(0.199)	(0.229)	(0.229)	(0.212)	(0.211)	(0.201)	(0.201)	(0.135)	(0.135)	(0.250)	(0.250)	(0.193)	(0.193)	(0.168)	(0.168)	(0.131)

Variances in parentheses

Table 2: OLS-estimated effect of using formal financial services on food insecurity experience (second step)

	(1) **formal_1**	(2) **formal_2**	(3) **formal_3**	(4) **save_only**	(5) **borr_only**	(6) **pay_only**	(7) **save_borr**	(8) **save_pay**	(9) **borr_pay**
treatment	-0.001 (0.005)	-0.026*** (0.007)	-0.024* (0.013)	-0.044*** (0.008)	0.046*** (0.008)	0.001 (0.006)	-0.033** (0.015)	-0.053*** (0.009)	0.026** (0.010)
inform	0.031*** (0.007)	0.026** (0.011)	-0.013 (0.029)	0.012 (0.014)	0.021 (0.015)	0.039*** (0.008)	0.058* (0.032)	0.026** (0.013)	0.016 (0.020)
account	-0.049*** (0.005)	-0.053*** (0.014)	-0.091 (0.069)	-0.082*** (0.011)	-0.033*** (0.009)	-0.025*** (0.007)	-0.033 (0.022)	-0.035 (0.025)	-0.049** (0.019)
woman	0.002 (0.005)	-0.009 (0.007)	-0.014 (0.012)	-0.003 (0.008)	-0.001 (0.008)	0.002 (0.006)	0.014 (0.014)	-0.014* (0.008)	-0.012 (0.010)
age	0.007*** (0.001)	0.005*** (0.001)	0.002 (0.003)	0.007*** (0.001)	0.006*** (0.001)	0.007*** (0.001)	0.004 (0.003)	0.003*** (0.001)	0.004** (0.002)
age_sq	-0.000*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000* (0.000)	-0.000*** (0.000)	-0.000** (0.000)
educ_23	-0.075*** (0.006)	-0.071*** (0.009)	-0.078*** (0.016)	-0.075*** (0.010)	-0.061*** (0.010)	-0.077*** (0.007)	-0.074*** (0.016)	-0.065*** (0.011)	-0.060*** (0.014)
emp_stat_46	0.006 (0.005)	0.010 (0.008)	0.030* (0.017)	0.010 (0.009)	0.008 (0.009)	0.005 (0.007)	-0.008 (0.017)	0.007 (0.010)	0.027** (0.013)
wid_div	0.035*** (0.010)	0.044*** (0.016)	0.031 (0.030)	0.030* (0.018)	0.032** (0.015)	0.036*** (0.012)	0.004 (0.031)	0.048** (0.020)	0.049** (0.022)
child_ratio	0.011*** (0.004)	0.004 (0.006)	0.009 (0.012)	0.012* (0.006)	0.011* (0.006)	0.010** (0.005)	0.030** (0.012)	0.004 (0.007)	0.003 (0.009)
ln_percap_income	-0.003 (0.003)	-0.008* (0.004)	-0.023** (0.009)	-0.003 (0.005)	0.004 (0.005)	-0.003 (0.004)	0.010 (0.009)	-0.010* (0.006)	-0.011* (0.007)
inc_q_2	-0.037*** (0.010)	-0.043*** (0.016)	0.000 (0.034)	-0.020 (0.018)	-0.054*** (0.014)	-0.039*** (0.012)	-0.102*** (0.030)	-0.018 (0.023)	-0.036* (0.022)
inc_q_3	-0.090*** (0.010)	-0.066*** (0.017)	-0.009 (0.034)	-0.057*** (0.019)	-0.133*** (0.015)	-0.086*** (0.013)	-0.126*** (0.032)	-0.035 (0.024)	-0.070*** (0.022)
inc_q_4	-0.151*** (0.011)	-0.122*** (0.018)	-0.051 (0.036)	-0.110*** (0.020)	-0.178*** (0.017)	-0.153*** (0.015)	-0.232*** (0.034)	-0.078*** (0.025)	-0.125*** (0.023)
inc_q_5	-0.207*** (0.013)	-0.191*** (0.020)	-0.116*** (0.041)	-0.163*** (0.022)	-0.229*** (0.021)	-0.212*** (0.016)	-0.278*** (0.039)	-0.157*** (0.028)	-0.172*** (0.027)
index_cm	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)
own_business	-0.058*** (0.006)	-0.039*** (0.009)	-0.029** (0.013)	-0.060*** (0.010)	-0.048*** (0.010)	-0.059*** (0.008)	-0.048*** (0.015)	-0.036*** (0.010)	-0.038*** (0.013)
Constant	0.931*** (0.044)	1.116*** (0.078)	0.791*** (0.205)	0.910*** (0.098)	0.728*** (0.072)	0.788*** (0.058)	1.137*** (0.111)	0.466*** (0.087)	0.787*** (0.227)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Nb. of observations	50,465	43,019	38,877	39,959	40,031	45,827	38,320	40,820	39,231
R-squared	0.317	0.280	0.292	0.320	0.322	0.317	0.328	0.273	0.323

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

Table 3: GLM-estimated marginal effect of using formal financial services on food insecurity experience (second step)

	(1) **formal_1**	(2) **formal_2**	(3) **formal_3**	(4) **save_only**	(5) **borr_only**	(6) **pay_only**	(7) **save_borr**	(8) **save_pay**	(9) **borr_pay**
treatment	-0.004 (0.006)	-0.033*** (0.008)	-0.027* (0.015)	-0.055*** (0.009)	0.053*** (0.010)	-0.003 (0.007)	-0.026* (0.016)	-0.060*** (0.010)	0.005 (0.012)
inform	0.038*** (0.008)	0.039** (0.015)	0.026 (0.037)	0.010 (0.016)	0.034** (0.017)	0.048*** (0.010)	0.052 (0.033)	0.058*** (0.017)	-0.008 (0.027)
account	-0.034*** (0.006)	-0.025* (0.013)	-0.094 (0.059)	-0.052*** (0.011)	-0.021* (0.011)	-0.013* (0.007)	-0.045** (0.019)	-0.002 (0.025)	-0.021 (0.018)
woman	0.006 (0.006)	-0.005 (0.008)	-0.028** (0.014)	-0.001 (0.009)	0.004 (0.009)	0.005 (0.007)	0.032** (0.015)	-0.014 (0.009)	-0.001 (0.012)
age	0.007*** (0.001)	0.006*** (0.001)	0.004 (0.003)	0.007*** (0.001)	0.005*** (0.002)	0.007*** (0.001)	0.008*** (0.003)	0.004** (0.001)	0.005** (0.002)
age_sq	-0.000*** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000** (0.000)
educ_23	-0.068*** (0.006)	-0.067*** (0.009)	-0.079*** (0.016)	-0.075*** (0.011)	-0.062*** (0.011)	-0.065*** (0.008)	-0.074*** (0.018)	-0.064*** (0.011)	-0.057*** (0.013)
emp_stat_46	0.006 (0.006)	0.008 (0.009)	0.039** (0.017)	-0.000 (0.010)	0.008 (0.011)	0.007 (0.007)	0.000 (0.019)	0.006 (0.010)	0.018 (0.014)
wid_div	0.019* (0.011)	0.030** (0.015)	0.023 (0.028)	0.008 (0.016)	0.015 (0.017)	0.028** (0.013)	-0.010 (0.029)	0.032* (0.017)	0.036 (0.022)
child_ratio	0.020*** (0.004)	0.013** (0.006)	0.023** (0.011)	0.024*** (0.007)	0.016** (0.007)	0.018*** (0.005)	0.047*** (0.014)	0.011* (0.006)	0.015 (0.009)
ln_percap_income	0.007** (0.003)	0.008* (0.005)	-0.003 (0.008)	0.009* (0.005)	0.010* (0.005)	0.008* (0.005)	0.021*** (0.007)	0.006 (0.006)	0.006 (0.007)
inc_q_2	-0.062*** (0.010)	-0.061*** (0.015)	-0.026 (0.029)	-0.067*** (0.018)	-0.067*** (0.015)	-0.064*** (0.013)	-0.132*** (0.025)	-0.055*** (0.021)	-0.034* (0.020)
inc_q_3	-0.113*** (0.011)	-0.093*** (0.017)	-0.036 (0.031)	-0.096*** (0.020)	-0.136*** (0.017)	-0.116*** (0.015)	-0.153*** (0.027)	-0.075*** (0.022)	-0.087*** (0.022)
inc_q_4	-0.181*** (0.012)	-0.159*** (0.018)	-0.091*** (0.034)	-0.163*** (0.021)	-0.185*** (0.020)	-0.187*** (0.017)	-0.265*** (0.030)	-0.137*** (0.024)	-0.142*** (0.024)
inc_q_5	-0.244*** (0.015)	-0.239*** (0.022)	-0.174*** (0.041)	-0.217*** (0.025)	-0.244*** (0.024)	-0.253*** (0.019)	-0.326*** (0.036)	-0.220*** (0.029)	-0.204*** (0.030)
index_cm	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
own_business	-0.061*** (0.007)	-0.047*** (0.009)	-0.037*** (0.014)	-0.079*** (0.011)	-0.063*** (0.011)	-0.054*** (0.009)	-0.063*** (0.017)	-0.043*** (0.011)	-0.038*** (0.014)
Constant	0.236 (0.209)	0.233 (0.461)	1.324 (0.877)	0.425 (0.593)	0.385 (0.367)	0.130 (0.243)	-0.540 (1.129)	0.858 (0.558)	-0.427 (0.677)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Nb. of observations	50,465	43,019	38,877	39,959	40,031	45,827	38,320	40,820	39,231
AIC	0.428	0.179	0.0443	0.0919	0.111	0.300	0.0299	0.105	0.0646

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

Table 4: PSM and FILM-estimated effect of using formal financial services on food insecurity experience

Treatment variables *Variables in lines (3) – (8) are exclusive*		**1-to-3 matching on propensity scores (caliper set to 0.2)** **Obs. on common support** Treated	Control	**ATT** (S.E.[10])	**Absolute bias reduction** Pseudo R2[11] Before	After	**Hidden Bias** (Γ)[12]	**FILM** **Obs. on common support** Treated	Control	**ATT** (S.E.)	**Test of no heterogeneous effects** F-statistic	p-value
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(i)	formal_1	12,751	37,676	-0.001 (0.007)	0.312	0.001	1.1	12,946	38,690	-0.001 (0.005)	2.626	0.000
(ii)	formal_2	5,319	37,676	-0.035*** (0.012)	0.515	0.002	1.4	5,380	38,690	-0.036*** (0.007)	6.345	0.000
(iii)	formal_3	1,195	35,348	-0.050** (0.022)	0.515	0.009	1.4	1,189	38,690	-0.043*** (0.011)	25.843	0.000
(iv)	save_only	2,283	37,676	-0.037*** (0.011)	0.301	0.001	1.4	2,313	38,690	-0.050*** (0.008)	3.732	0.000
(v)	borr_ only	2,355	36,361	0.032*** (0.011)	0.102	0.000	1.0	2,384	38,690	0.044*** (0.008)	8.002	0.000
(vi)	pay_ only	8,139	37,676	-0.003 (0.009)	0.373	0.001	1.1	8,243	38,690	0.000 (0.006)	2.373	0.000
(vii)	save_borr	644	33,360	-0.037* (0.018)	0.314	0.003	1.3	658	38,690	-0.028* (0.012)	41.658	0.000
(viii)	save_pay	3,127	37,676	-0.047*** (0.016)	0.523	0.003	1.6	3,148	38,690	-0.073*** (0.008)	12.851	0.000
(ix)	borr_pay	1,551	36,407	0.024 (0.014)	0.424	0.001	1.1	1,570	38,690	0.033*** (0.009)	25.645	0.000

[10] Bootstrapped Standard Errors with 100 replications.
[11] The Pseudo R2 indicates the goodness of fit of the logit regression after (only on the matched sample) the matching procedure.
[12] The Hidden Bias (Γ) reports the critical value of gamma at which result would have to be questioned, calculated using Rosenbaum bounds sensitivity analysis.

Conclusion

This paper contributes to the empirical evidence on the impact of using a range of different formal financial services, including savings, credit and payment services, on the food insecurity experienced by rural populations of low-and middle-income countries. This empirical exercise was motivated by the view that use of different financial services could – on one hand – improve the individual's income, consumption, and thus improve the personal experience of food security but – on the other hand – could be suboptimal in the sense that it imposes costs that negatively impacting the individual's personal experience of food security.

To empirically test the impact of financial services on food security experience, we relied on cross-sectional individual-level data from Gallup World Poll 2014-survey and non-experimental methods addressing the issue of selection bias due to non-random treatment assignment: entropy balancing, propensity score matching and fully interacting linear matching. Food Insecurity Experience Scale (FIES) indicator, our outcome variable, fills a gap in the efforts to capture the fundamental nature of food security condition and in a manner that allows for cross-country comparisons.

Results suggest that, depending on the type of service being used, financial services can have different impacts on food security in rural areas of low-and middle-income countries. Among the examined three financial products only saving services – whether they are used alone or combined with credit and payment services – reduce the individual's probability of experiencing food insecurity. When savings are absent, use of payment services has no effect on food insecurity and taking a loan increases significantly the individual's probability of experiencing food insecurity.

Such findings suggest that the type of financial product matters in determining individual's food insecurity experience. First of all, payment services are commonly used as the means to make daily transactions, and the payment mean itself does not seem to be a feature that affects considerations shaping the individual's food security experience..

Existence of savings in case of unexpected events can make the individual feel less food insecure. The literature shows that household savings can contribute to a greater sense of material security, which strengthens household's resilience and encourages in undertaking productive risks (Sodha and Lister, 2006; Karlan *et al.,* 2014). In addition, savings formally offer higher rates of return, quicker access to funds, and greater anonymity (Vonderlack and Schreiner, 2002) – all that to improve income level and ensure household's consumption. When savings are absent, use of credit can be a common and immediate solution to get the needed financial resources (Sodha and Lister, 2006). However, repayment of the loan and interest on it can reduce the budget available to meet household's consumption needs, which can endanger food security of household members when the burden of debt repayment is too unbearable. In the long run, such an individual is particularly vulnerable to fall into the poverty trap, especially if the decision to borrow is driven by lack of own assets.

In our sample, individuals obtained the loan within 12 months prior to the survey and in majority of cases was used for business, housing and education. Such behaviour first of all reflects the reality of rural areas where access to formal financial services is limited and credit is provided only to the solvent clients with economically viable investment projects. The debtor still has to prove a sufficient income to pay back a long-term engagement with the financial institution and often needs to complement the investment with own resources, which can place especially at the beginning a great burden on household's income and make the individuals feel food insecure due to uncertainty in their ability to buy food. However, further research is needed to verify the long-term effects of financial inclusion on food security experience and on other individuals' perceptions of well-being.

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Appendix

Table 1: Definition and descriptive statistics of control variables

Variable name	Description
inform	Dummy for using informal financial services
account	Dummy for having an account including account at a financial institution or mobile money account.
woman	Dummy for being a woman.
age	Respondent's age
age_sq	Age in square
educ_23	Dummy for completed at least secondary education.
emp_stat_46	Dummy for being unemployed or out of workforce.
wid_div	Dummy for being widowed or divorced.
child_ratio	Proportion of children in the household calculated as number of children divided by number of household members
ln_percap_income	Natural logarithm of household income per capita converted to International Dollars (ID) using purchasing power parity (PPP) ratios.
inc_q_2 inc_q_3 inc_q_4 inc_q_5	Dummies for within-country quintile group to which individual belongs depending on his/her household income per capita. The lowest income quintile indicates the poorest 20% of the country's population, and the highest income quintile indicates the richest 20% of country's population.
index_cm	Communications Index calculated by Gallup World Poll to assess the degree to which respondents are connected via electronic communications.
own_business	Dummy for currently owning a business.

Figure 1: Distribution of outcome variable: probability of experiencing moderate or more food insecurity

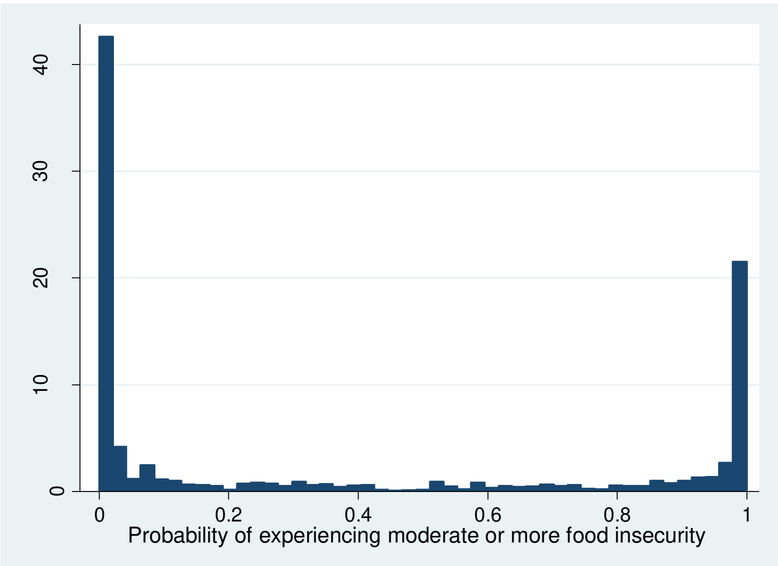

Table 2: Descriptive statistics of probability of experiencing moderate or more food insecurity by different treatment sub-groups

Treatment variables	Treated group			Control group			Difference in sample means
	Nb. of obs.	Mean	SD	Nb. of obs.	Mean	SD	t-test
formal_1	12,968	0.315	0.414	38,690	0.425	0.440	-0.111***
formal_2	5,420	0.241	0.377				-0.184***
formal_3	1,216	0.233	0.377				-0.193***
save_only	2,318	0.238	0.382				-0.187***
borr_only	2,384	0.368	0.428				-0.057***
pay_only	8,266	0.320	0.416				-0.105***
save_borr	658	0.238	0.381				-0.187***
save_pay	3,191	0.222	0.365				-0.203***
borr_pay	1,571	0.280	0.395				-0.145***

Figure 2: Logit estimates of propensity scores

VARIABLES	(1) formal_1	(2) formal_2	(3) formal_3	(4) save_only	(5) borr_ only	(6) pay_ only	(7) save_borr	(8) save_pay	(9) borr_pay
informal	0.795***	1.249***	1.863***	0.835***	0.798***	0.794***	1.092***	1.374***	1.123***
	(0.041)	(0.081)	(0.206)	(0.084)	(0.082)	(0.051)	(0.190)	(0.105)	(0.138)
account	2.832***	4.535***	6.036***	3.015***	1.082***	3.514***	3.920***	5.377***	4.047***
	(0.030)	(0.073)	(0.323)	(0.064)	(0.055)	(0.041)	(0.142)	(0.139)	(0.106)
woman	0.037	-0.053	-0.114	-0.059	0.052	0.034	0.180*	-0.149***	-0.025
	(0.027)	(0.045)	(0.083)	(0.052)	(0.047)	(0.034)	(0.094)	(0.057)	(0.067)
age	0.042***	0.054***	0.168***	0.008	0.123***	0.014***	0.061***	0.015*	0.128***
	(0.004)	(0.007)	(0.018)	(0.008)	(0.008)	(0.005)	(0.016)	(0.009)	(0.013)
age_sq	-0.000***	-0.001***	-0.002***	-0.000	-0.001***	-0.000***	-0.001***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
educ_23	0.197***	0.545***	0.691***	0.140**	0.115**	0.250***	-0.001	0.754***	0.496***
	(0.031)	(0.053)	(0.103)	(0.058)	(0.055)	(0.040)	(0.104)	(0.068)	(0.084)
emp_stat_46	-0.317***	-0.871***	-1.124***	-0.108*	-0.203***	-0.473***	-0.443***	-0.851***	-1.154***
	(0.030)	(0.051)	(0.104)	(0.059)	(0.053)	(0.038)	(0.114)	(0.065)	(0.081)
wid_div	0.160***	0.387***	0.530***	0.239**	0.308***	0.131**	0.248	0.501***	0.421***
	(0.052)	(0.087)	(0.172)	(0.100)	(0.086)	(0.066)	(0.189)	(0.110)	(0.132)
child_ratio	-0.076***	-0.174***	-0.254***	-0.103***	-0.105***	-0.063**	-0.165**	-0.176***	-0.208***
	(0.021)	(0.034)	(0.067)	(0.039)	(0.037)	(0.026)	(0.082)	(0.042)	(0.054)
ln_percap_income	0.046***	0.061***	0.238***	-0.044*	0.053**	0.060***	0.012	0.022	0.072*
	(0.013)	(0.023)	(0.056)	(0.026)	(0.026)	(0.016)	(0.052)	(0.029)	(0.037)
inc_q_2	-0.018	0.047	0.010	0.255**	0.055	-0.086	0.120	0.312**	-0.050
	(0.048)	(0.091)	(0.198)	(0.109)	(0.078)	(0.062)	(0.181)	(0.130)	(0.130)
inc_q_3	0.061	0.259***	0.328	0.593***	0.067	-0.051	0.523***	0.563***	0.042
	(0.052)	(0.095)	(0.200)	(0.114)	(0.086)	(0.067)	(0.187)	(0.136)	(0.136)
inc_q_4	0.125**	0.451***	0.430**	0.777***	0.002	0.084	0.355*	0.954***	0.155
	(0.057)	(0.102)	(0.214)	(0.122)	(0.097)	(0.072)	(0.209)	(0.144)	(0.147)
inc_q_5	0.222***	0.796***	0.845***	1.171***	-0.089	0.138*	0.521**	1.434***	0.396**
	(0.066)	(0.117)	(0.250)	(0.138)	(0.115)	(0.084)	(0.243)	(0.164)	(0.171)
index_cm	0.006***	0.009***	0.014***	0.005***	0.003***	0.007***	0.002	0.011***	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
own_business	0.139***	-0.005	0.121	0.438***	0.524***	-0.238***	0.710***	-0.126*	-0.241***
	(0.036)	(0.055)	(0.092)	(0.063)	(0.059)	(0.048)	(0.104)	(0.068)	(0.085)
Constant	-3.408***	-7.915***	-17.256***	-7.312***	-8.398***	-2.956***	-10.317***	-9.327***	-9.034***
	(0.154)	(0.333)	(1.190)	(0.631)	(0.554)	(0.181)	(1.120)	(0.422)	(0.474)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	52,229	44,526	37,854	41,392	40,127	47,467	35,065	42,260	39,321
Pseudo_R2	0.341	0.563	0.604	0.336	0.178	0.439	0.384	0.602	0.490

Standard errors in parentheses
* Significant at 10 %; ** Significant at 5 %; *** Significant at 1 %. Robust standard errors are reported