Givers of great dinners know few enemies: The impact of household food security on micro-level communal conflict in Eastern Democratic Republic of Congo

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Abstract

This study establishes a direct linkage between household level food security and food benevolence with the reduction of conflict using novel data from 1763 households of North Kivu, Democratic Republic of Congo. Using propensity score matching, we find that food security decreases conflict with other households by up to 10 percentage points and conflict against groups within the community by around 4 percentage points. Furthermore, households that help others with food experience a further reduction of up to 24 percentage points in conflict against individual households and 5.3 percentage points in conflict against groups. The findings indicate that benevolence towards others may be a potential channel through which food security reduces household level conflict. Our results hold through a rigorous set of robustness checks including a doubly robust estimator, placebo regression, matching quality tests and Rosenbaum bounds for hidden bias. We conclude by recommending more food security programs for micro-level conflict mitigation by promoting benevolence and social cohesion among community members.

Keywords: Conflict, Food Security, Propensity Score Matching

JEL Codes: D7, O11,

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1. INTRODUCTION

Historical accounts of food shortages causing conflict can be traced back to the Russian and French Revolutions of the 17th and 18th century. In modern times, prevalence of hunger has been documented to drive violent behavior and conflict between and within communities through environmental, social, economic, and political channels (see for e.g. Bora et al., 2010; World Bank, 2011). Due to the complexity of establishing a direct relationship between hunger and conflict, the more popular academic approach of investigation has been through the aforementioned channels and almost entirely confined to macro or district level analyses. Examples include the causal linkage between climate change and conflict with food shortage as an underlying cause (Miguel, Satyanath, & Sergenti, 2004; Burke, Miguel et al., 2009; Barnett Adger, 2007; Salehyan, 2008); poverty and grievance driven by hunger and malnutrition, causing civil conflict (Collier, 2004; Pinstrup-Andersen & Shimokawa, 2008); and extreme volatility in food prices and acute food shortages triggering conflict (Berazneva & Lee, 2013; Arezki & Brückner, 2011; Bessler, Kibriya et al., 2016; Bellemare 2015; Bush & Martiniello, 2017).[3] While these studies strongly establish hunger as one of the drivers of conflict at a national or subnational level, there has been limited research at a household level which could provide insights into the behavioral or psychological channels through which food security and conflict may be related. The most recent literature appearing in this issue addresses this literary gap by investigating the relationship between household nutrition and conflict (Sneyers, 2017); violence exposure and household food deprivation (Mercier, et al., 2017); and conflict, household resilience and food security (Brück, D'Errico, & Pietrelli, 2017). We strengthen this novel collection of scholarship by establishing a linkage between household level food security and benevolence on individual and community level conflict with primary survey data collected from Beni, Lubero and Rutshuru territories of North Kivu, Democratic Republic of Congo (DRC).

[3] Other variables related to food security that have been connected to economic and political marginalization, civil and communal conflict include competition over resources, access to cooking fuel, poverty, lack of educational access and material rewards, poor health and nutrition, and the presence of young adults (see Brinkman & Hendrix, 2011, for a comprehensive review).

Recently, scholars have acknowledged this need for micro-level analyses to capture the specific responses of households due to psychological or behavioral differences emanating from food security. For example, in this issue Weezel (2017) recognizes that while national-level data can be useful in predicting trends, some information is lost due to aggregation. Therefore, he recommends using micro-level data to gain a better understanding of the specific mechanisms that lead to the complex dynamics between food security and conflict. Similarly, the survey paper by Martin-Shields & Stojetz (2017) points out that micro-empirical studies typically use a crude measure of household conflict - proximity to battle grounds and violence. While these measures may provide some indication of a household's exposure to conflict clearly there is a need for better measurement of micro-level experiences of households. Furthermore, civil war or violent events data through media reports may not be sufficient to capture violence at an individual or community level.

To capture such individual and community level incidences of conflict, we use survey data from 1763 households. We argue that food security can reduce the conflict experienced by a household in two ways. First, a food secure household will have a lower propensity to get involved in conflict. This may be due to fewer incentives and higher opportunity cost of engaging in conflict. Second, if such a household chooses to assist others with food it may attain a higher social status and can engage in society in a more cohesive manner, thus avoiding conflict. We investigate two specific questions: i) are food secure households less likely to engage in individual and community level conflict? And ii) is there a further reduction in the probability of engaging in conflict by a subset of these households that also provide food assistance to fellow community members? Our attempt stands to make three unique contributions. First, extant literature is inclined to explore the linkages between hunger (or food *in*security) and conflict; a very subtle deviation from the policy manifesto of "food security to reduce conflict". We test the actual policy recommendation as opposed to the counterfactual. Second, as relevant literature on food security and conflict moves from cross country correlations to local levels, we are one of the first to consider household and community level violence. Third, we investigate the role of social cohesion on reducing conflict through food benevolence.

To successfully answer this research query it was important that our contextual region had prevalent food insecurity and different scenarios of individual and community level conflict. One such region with these existing socio-political conditions is the Democratic Republic of Congo. DRC is one of the seven countries in the world that make up sixty-five percent of the world's food insecure people (Brinkman & Hendrix, 2011). Additionally, being rich in natural resources, DRC has many rebel groups, thereby making the country even more conducive to inequality and conflict. The past few years have seen the Congolese government combatting armed rebel forces, especially in the eastern province of North Kivu which shares its borders with Rwanda, Uganda, and Burundi - countries that have themselves been subject to civil war and conflict. Hence, given the unfortunate confluence of pervasive hunger, inequality and conflict, North Kivu in DRC serves as an ideal setting to conduct such an analysis.

To estimate the causal effects of food security on household level conflict, we employ the quasi-experimental estimation technique of propensity score matching (PSM). We test the robustness of our findings with different matching techniques and tests of covariate balance as well as estimating our results using a doubly robust estimator. Our quasi-experimental setup offers several benefits. First, we avoid the requirement of baseline data on households who have become food insecure (Imbens & Woolridge, 2009). Second, we ensure that the comparison of the outcome variable, conflict, is undertaken between households with similar characteristics (Dehejia & Wahba, 2002). Third, when comparing sub-populations of households with similar characteristics, covariates are independent of food insecure households, and thus a causal interpretation of the results is reasonable (Imbens & Woolridge, 2009).

Overall, we find that a household's food security reduces its probability of conflict with other households and with groups within the community. In addition, food secure households that assist others with food experience a further reduction in conflict. Benevolence thus provides a potential channel through which food secure households are able to build social status, cohesion and respect to avoid conflict. Although we have tried to control for various sources of bias, given the complex relationship between food security and conflict, we show extreme caution to claim causality. However, at a minimum, our results establish the micro-foundational linkage scarce in

the literature as well as provide evidence of food benevolence as a possible behavioral pathway through which food security may reduce household level conflict.

The remainder of the paper is organized as follows: section 2 describes the study justification and context; section 3 explains the sampling strategy and data and describes the variables; section 4 develops an empirical model and identification strategy. Section 5 presents the results and discusses our main findings while section 6 concludes the paper.

2. STUDY JUSTIFICATION AND CONTEXT

(a) Study justification

Food insecurity created from a lack of production, market access and high prices are exacerbated by political and economic marginalization of certain groups. Such conditions translate to a feeling of steep horizontal inequality (Qstby, 2008; Stewart, 2011) leading to violent reactions. On the other hand, evidence from Nepal and South Sudan suggest that food security can enhance a feeling of equality and harmony at a communal level (McCandless, 2012). At a household level, food security should provide members with a sense of parity and confidence in the local government which can curtail violent reactions. Lack of feelings of injustice is reason enough for them to not join a rebellion, rebel group or engage in disagreements with government forces. Conversely, food insecurity can provide individuals and households with both material and non-material incentives to engage in any form of anti-social behavior (Martin-Shields & Stoetz, 2017). Food secure households in an impoverished society are also likely to have better access to education and employment which makes the opportunity cost of joining a movement higher (Taeb, 2004). Additionally, in the presence of rebel forces, citizens who are food insecure may be lured to joining violent groups to obtain food and shelter (Bermen, 2011), while their more stable counterparts lack such incentives. Internally Displaced People (IDPs) are generally more food insecure and prone to conflict (World Bank, 2011; Taeb,

2004). However, food secure households are less likely to get displaced and fall into the conflict trap.

At a communal level, food security lowers the probability of risk of violence by increasing social cohesion and participation (Brinkman & Hendrix, 2013; Fearon et al., 2009). Food secure households are likely to take a more participatory role in community leadership and increase social cohesion. These households are also able to assist less fortunate members of the community with food. Due to their status and behavior within the community, it is expected that they will garner more power and a higher social standing. Social revolution theorists argue that an individual's discontent or grievance based on social class can lead to rebellion (see Humphreys & Weinstein, 2008). Empowered households are therefore less likely to engage in personal and community level conflict.

Food insecurity can also cause undue competition for resources such as water and land which may lead to personal (Messer, 1998; Cohen & Pinstrup-Anderson, 1999) and community level conflict (Homer-Dixon, 1999; Kahl, 2006). Lack of access to land and water resources often create conflict between farmers and pastoralists (Hendrix & Salehyan, 2010; Schomerus & Allen, 2010). While such conflict between pastoralists and farmers due to land encroachment and water resources are more common against a backdrop of hunger (Raleigh, 2010), food security ensures less cattle raiding and altercation over resources (Schomerus & Allen, 2010). Households with higher status are likely to have greater access to resources. Conflict between agricultural communities and rebel groups over food and resource at both community and individual level is quite common in African societies (Macrae & Zwi 1992; Richards, 1998; Winne, 2010). Rebel groups and insurgents acquire resources and food by looting farming households and competing with them over resources (Pottier, 2003; Taeb, 2004). However, a food affluent household can avert such conflict in two different ways; a. they can meet the demands of rebel groups in a non-violent manner; and b. due to their higher social standing and connections, rebel groups may choose to avoid challenging them.

To summarize, we identify several channels through which food security can potentially reduce lower intensity conflict at the household level. These include: a) being satisfied and content; b) improving social resilience, cohesion, and status; c) reducing incentive and increasing opportunity costs of joining a rebellion; d) lowering prospects of altercations over resources; e) lowering the possibility of being displaced and f) enabling them to settle disputes in a peaceful manner. If such households help individuals and groups with food, their propensity to experience conflict may be even lower due to three additional reasons: a) by obtaining popularity and respect; b) by settling potential conflict peacefully through food aid; and c) their social power may deter would-be perpetrators from engaging with them in a bellicose manner.

(b) Study Context

Despite being one of the most resource rich countries in the world, the Democratic Republic of Congo is plagued by inequality and poverty, rebel groups, unstable governments, weak property rights, competition over resources, food insecurity and land displacement. According to the International Fund for Agriculture Development (extracted April, 2016), about 70 percent of the employed population is engaged in agriculture, mostly for subsistence. Being one of the poorest countries in the world, DRC was ranked 176 out of 188 countries on the 2016 United Nations Human Development Index. UN country data estimated DRC's population to be about 80 million in 2016 with around 47% living below the national poverty line (WFP, 2014). The World Food Programme (WFP) also states that over 6 million people are living in conditions of acute food insecurity and livelihood crisis. The UN (2015) estimates about 2.2 million internally displaced people (IDPs) living in DRC. Of the close to one million people that have been displaced in North Kivu, around 17% have been in the territory of Beni, 16% in Lubero and 11% in Rutshuru (UN, 2015). The major cause of displacement remains armed conflicts and ongoing operations.

After serving as a Belgian colony for almost a century (1870 - 1960), Congo gained independence in 1960. However, the period following independence has been marked by

extreme corruption, exploitation and political instability. Between 1990 and 1994 civil war broke out in the neighboring country of Rwanda which left a lasting impact on DRC. Following the Rwandan genocides of 1994, a lot of the marginalized population fled to eastern DRC (then known as Zaire) to refugee camps established along the border. Rwandan militia forces followed them into DRC and this entry ignited the Congolese wars. Between 1996 and 1997 Rwandan and Ugandan armed forces formed a coalition to overthrow the government of Zaire (under Mobutu's rule) in an attempt to control mineral resources, thus leading to the first Congolese war. They succeeded in overthrowing the government but the new leader, Laurent-Désiré Kabila urged the armed forces to leave the country. Although the armed forces left DRC, newly formed rebel groups from Rwanda and Uganda instigated the second Congolese war in 1998 in an attempt to overthrow Kabila. While the second civil war officially ended in 2003, armed conflict continues between the military of DRC and Rwanda, and the rebel forces of the Democratic Forces for the Liberation of Rwanda (FDLR) remaining in DRC[4].

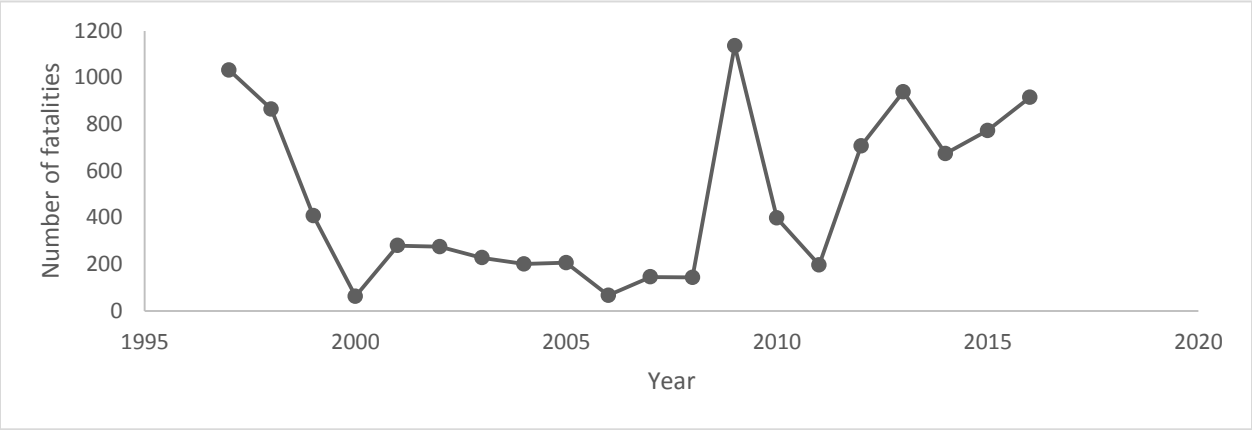

Figure 1: *Conflict trend in North Kivu between 1997-2016*
Source: Authors' own calculations based on ACLED data

Figure 1 provides an overview of the conflict trend in North Kivu over the past two decades. With borders shared with Rwanda and Uganda, North Kivu has been at the heart of conflict in DRC. Since the communal violence that started locally in North Kivu in 1993

[4] More than 70 percent of the combatants were deported to Rwanda through the United Nations after 2003.

transitioned into a full blown national war, at least two dozen armed rebel groups have formed in the region. Even at present, the province poses the greatest threats to political stability in DRC (see Stearns, 2012; Vlasseroot & Huggins, 2005; and Vlassenroot and Raeymaekers, 2008 for a detailed account of the conflict in North Kivu).

The multitude of armed groups still active in the province, such as the FDLR, the Allied Democratic Forces (ADF) and various Mayi-Mayi militias, continue to rebel against the DRC authorities and sporadically attack vulnerable civilians. The government's armed forces (FARDC) are also reported to clash with civilians. Such violence also creates a lack of social governance, stability and cohesion among local households creating further micro-level conflicts. Many if not all these clashes involve and deplete natural resources and food. In 2014, WFP reported 2.7 million people in North Kivu were food insecure many of whom were conflict prone as well. Given this context and the ongoing history of conflict between government forces, multiple rebel groups and civilians in the region, North Kivu is an ideal setting for our study.

3. DATA DESCRIPTION

(a) Survey design and data collection

During July 2014, The Howard G. Buffett Foundation funded and initiated the data collection for this research through Texas A&M University, as part of its Best Practices in Coffee and Cacao Production (BPCC) Project. The authors of this paper contributed to the survey design and information collection procedure that ensured pertinent sample population and specific survey questions related to this study.

As mentioned, the data for this study was collected from the province of North Kivu, Eastern DRC. The present administrative units of the region is divided into six territories (or zones). Our survey was conducted in three of these territories– Beni, Lubero and Rutshuru. Villages were selected randomly from each of these territories. High-resolution maps from the United Nation's

Office for the Coordination of Humanitarian Affairs (UNOCHA) were used to get a detailed account of the villages (see Figures 3 to 6 in the Appendix). The statistical software "R" was used to generate random numbers to select villages for sampling. This ensured that every village had equal probability of being selected for our study. Every household in selected villages were interviewed. Through this process, we were able to identify 48 villages and obtain a full sample of data from 1763 households. A household was defined as a group of people sleeping under the same roof and eating together. Local extension agents, employed as enumerators, were instructed to ask for the individual responsible for farming. If the individual was not available, enumerators would proceed to the next house and return later.

Structured questionnaires were used to gather information on household socio-economic and demographic structure, food security measures, conflict incidents, land access patterns, access to markets and knowledge, access to basic services, cooperative membership and social cohesion and empowerment. The questionnaire was translated to French, the commonly spoken local language of North Kivu, and pilot tested before actual surveys took place. The responses were translated back to English before being coded. The interviews took place in a one on one setting to maintain confidentiality of the participants. Due to the low education levels and high rate of illiteracy in the region, interviewers sought oral consent by guaranteeing the respondents confidentiality and ensuring their names were not recorded. Each participant was distinguished by unique identification numbers (UIN). Respondents did not receive any compensation for participating in the study.

(b) Variables

The unit of analysis for this study is the household. The outcome variable of interest is conflict experienced by households. To measure conflict, households were asked which, if any, of the following types of conflict they experienced in the past six months – a) conflict with neighbors and fellow villagers; b) disagreement involving Virunga park; c) landholder reclaimed occupied land; d) border conflict with landholder; e) dispute among non-dwelling family members f) occupied land granted to a new tenant; g) disagreement with pastoralists; h) conflict over community resources and agricultural inputs; i) resource conflict with rebel forces; j) land

conflict with rebel forces; k) land conflict with government; l) resource conflict with government forces; m) other kinds of conflict with government forces; and n) any other kind of conflict that they were asked to specify. Focus group discussions with community members prior to the household interviews helped us identify the above-mentioned types of conflict as the most prevalent in our areas of study.

Using household responses of conflict experienced, we constructed four alternative measures of conflict: a) *conflict* is an indicator variable equal to one if the household has experienced any type of conflict with any party and zero otherwise; b) *conflict with individuals* is an indicator variable equal to one if the household has experienced conflict with other individual households such as neighboring households or fellow villagers, conflict with landholders or with non-dwelling relatives and zero otherwise; c) *conflict with groups* is an indicator variable equal to one if the household has experienced conflict with the community over public resources, conflict with government forces or with rebel forces and zero otherwise; and d) *types of conflict* is a count variable that aggregates the total number of conflict types the household has encountered.

The main explanatory variable is household level food security. We used the United States Department of Agriculture (USDA) definition and measurement of food security (extracted 2017). USDA defines a household to be highly food secure if it reports that it has "no problems, or anxiety about, consistently accessing adequate food". Following this definition, we asked the household the following question, "how often have you had difficulty feeding your entire family in the last six months?" The respondents could choose between three options, namely, "often", "sometimes" or "never". For our analysis, we categorize a household as food secure if it responded "never"; and food insecure if it responded "often" or "sometimes". Additionally, to test for the effect of *benevolence*, we asked households if they had helped others with food in the past six months. Households that answered positively were classified as *benevolent* and households that responded negatively were categorized as *non-benevolent*.

Control variables included village specifications and basic household demographics such as religion, household size, number of adult males in the household, education, income, access to markets and information, access to water and cooking fuel, social empowerment and voice in the

community, land ownership status, and membership in cooperatives. Household size is included since larger households may have a greater likelihood of being involved in situations of conflict or depending upon adult members will have varying degree of food security. Education, which may reduce both food insecurity and conflict, is accounted for through the years of education of the most highly educated member of the household. The variable is used both in linear and quadratic forms. The link between poverty and conflict has long been established in the conflict literature. Hence we control for household income; access to basic services such as drinking water and cooking firewood; and access to information and technologies which may provide information about markets or current situations of conflict such as radio/television/cell phone/internet; as well as access to bicycle or motorized vehicles. More influential households may face lesser food insecurity or conflict; hence we control for various measures of empowerment and voice. Finally, we control for religion and village specific characteristics.

(c) Descriptive statistics

Table 1 presents a cross tabulation of the types of conflict incurred by households and their food security status. For example, 429 food secure households reported to being involved in some kind of conflict with other households compared to 781 food insecure households that reported the same. However, it should be noted that the number of food secure and food insecure households are not equal in our sample and that some households reported to having experienced conflict with more than one party. As a result, the difference in numbers should be interpreted with caution and have been presented merely to give a sense of the distribution of the two key variables in the data.

Table 1: *Number of households reporting each type of conflict*

	Number of households	
Type of conflict reported	Food secure	Food insecure
Conflict with individual households	429	781
Conflict with groups	96	222
Total	525	1003

Source: Authors' calculations based on the survey data.
Note: A single household may incur more than one type of conflict.

Table 2 presents the socioeconomic characteristics of households by food security status as well as means for the full sample. The first three dependent variables can be interpreted as the proportion of households that experienced conflict. About 43% of the sample households assessed themselves as being food secure while the remaining 56% reported to have been food insecure. This is consistent with a WFP report on food security in DRC by province which classifies around 50% households in North Kivu as food secure (WFP, 2014). Around two-thirds of all households help others with food.

Overall, about 50% of the sample households reported having experienced some form of conflict. Approximately 41% were involved in conflicts with other households, while 9% incurred conflict with the community. While many households reported to suffering from violence or disagreement with multiple parties (between one and twelve different types), the average number of conflicts experienced by a household is reduced to around one due to half of the sample households not having experienced any conflict. The most common type of conflict occurred with other households such as neighbors and fellow villagers in the community; while the next most prominent types involved landholders and pastoralists.

The average household in our sample has around five members with the most educated member in the household having around nine years of education. The monthly per capita income for a typical household is 17,600 Congolese Francs (CDF)[5]. This translates to less than US $1/day, which is below the World Bank's 2013 estimate of international poverty line of US $1.90/day (World Bank, 2016). The annual household income per capita for our sample was thus around US $228/year in 2014. Around 60% of the respondents do not hold written land claims over their land, did not receive any agricultural extension service and lack access to safe drinking water and cooking fuel. About a fifth of the sample population belong to a cooperative and three quarters of the respondents have access to some form of technology. 93% of the respondent households have held some kind of leadership position in the community.

The results also show that food secure households are different from food insecure households in terms of socioeconomic and demographic characteristics. For example, the

[5] 1 USD=925 CDF at the time of the study.

average food secure household is significantly larger, comprised of more adult males, has attained a higher level of education and earns more household income than food insecure households. Furthermore, food secure households have significantly greater access to technology such as mobile phones, radio, television or internet as well as access to vehicles such as bicycles and motorcycles. They are also more likely to hold leadership positions in the community and exhibit benevolence towards others. Food security status had significant variation among villages, though these have been omitted from our display due to space constraints. Access to agricultural extension services, access to cooking fuel and membership in cooperatives were higher but statistically insignificant for the average food secure household.

Table 2. *Summary statistics of main variables*

Variable	Food secure households (N=762)	Food insecure households (N=1001)	All households (N=1763)
Dependent variables			
Probability of conflict	0.46***	0.54	0.50
Probability of conflict with individual households	0.36***	0.45	0.41
Probability of conflict with groups	0.09	0.09	0.09
Types of conflict incurred	0.73***	1.03	0.90
Independent variables			
Household size (members)	5.45*	5.23	5.33
Number of adult males	2.24**	2.10	2.16
Education (number of years)	9.48***	8.83	9.11
Education squared	111.67***	99.42	104.67
Household income (`000 CDF/capita)	19.3*	16.4	17.6
Respondent has written land claim (yes=1)	0.37***	0.43	0.40
Access to technology and markets (yes=1)	0.84***	0.69	0.75
Lack of extension services (yes=1)	0.60	0.62	0.61
Cooperative membership (yes=1)	0.23	0.21	0.21
Access to safe drinking water (yes=1)	0.63	0.63	0.63
Inadequate access to cooking fuel (yes=1)	0.56	0.64	0.61
Leadership position (yes=1)	0.95***	0.91	0.93
Household is benevolent with food (yes=1)	0.78***	0.63	0.69

Source: Authors' calculations based on the survey data.
Notes: We used t-tests to test for equal means between food secure and insecure households. *, **, and *** indicate significance at 10%, 5% and 1% levels respectively. Village and religion specific dummies have been omitted from the table to save space. CDF=Congolese Franc.

4. MODEL IDENTIFICATION STRATEGY

(a) *Estimation of treatment effects*

The complex relationship between food security and conflict immediately points to potential endogeneity bias in estimation. Therefore, to estimate causal impacts, we use food security as a 'treatment' and test whether this treatment can reduce the probability of conflict for individual households. Henceforth in this paper we will use the terms food secure, treated and treatment group interchangeably. Similarly, we will interchange between the terms food insecure, control and control group.

Let T denote our binary treatment variable (T=1 if the household is food secure and T=0 otherwise). Let Y_1 denote the outcome (conflict status) of a household that is food secure and Y_0 the outcome for the same household had it not been food secure; let X be a vector of observable covariates (background characteristics or 'pretreatment' variables). If T could be randomly assigned to households, estimating the average treatment effects (ATE) would give us the causal impact of being food secure on conflict. However, such an experiment that entails providing food security to randomly assigned households is neither possible nor ethical. Since we cannot randomize an intervention to avoid selection bias, we are left with quasi-experimental techniques (see Cook, Shadish, & Wong, 2008) to improve (if not isolate) the estimates of the causal effect of food security on conflict. Two prominent approaches – instrumental variables and regression discontinuity – would be useful methods, but are difficult to employ. Valid instruments are difficult to identify (Imbens & Woolridge, 2009). Some possibilities exist, e.g. natural disasters, but require assumptions such as exogeneity of the instrument, that are particularly difficult to justify in this context. Regression discontinuity is another option but requires consistent decision-making around some arbitrary cutoff. In our case, food insecurity is unlikely to be allocated in such a way. Therefore, we employ a third quasi-experimental approach - propensity score matching - in which all observable confounding factors are statistically balanced to neutralize any potential selection bias, thus allowing us to isolate the causal effects of food security on conflict.

Intuitively speaking, an unbiased average effect of treatment on the treated (ATT) could be calculated as the difference in mean outcome for the treated given that they received treatment and the mean outcome for the treated had they not received treatment. However, this outcome of the treated had they not received treatment is the counterfactual which cannot be observed in reality. Matching aims to solve this problem by constructing the correct sample counterpart for the missing information on the outcomes of the treated group had they not been treated. In other words, it addresses the 'counterfactual' by pairing each participant in the treated group with similar participants in the control group and then estimating the ATT as the difference in mean outcomes between the two groups. This can be expressed as follows:

$$ATT = E(Y_1 - Y_0 | X, T = 1)$$

$$ATT = E[E(Y_1 | X, T = 1) - E(Y_0 | X, T = 1)]$$

$$ATT = \left[\underbrace{\left(E(Y_1 | T = 1) - E(Y_0 | T = 0)\right)}_{\textit{naïve estimator}} - \underbrace{(E(Y_0 | T = 1) - E(Y_0 | T = 0))}_{\textit{selection bias}}\right] \qquad (1)$$

Equation 1 shows how the ATT can provide correct estimates by adjusting for selection bias.

(b) *Propensity score matching (PSM) approach*

One way to implement matching could be to match treated and control households on every covariate. However, as more variables are added to the analysis, it becomes harder to find exact matches for observations. The propensity score matching technique, proposed by Rosenbaum and Rubin (1983), solves this 'curse of dimensions' by combing all confounders into a single score, the propensity score, and matching observations based on the propensity score alone. In this study, the propensity score is the conditional probability that a household will be food secure, given its vector of observed covariates. PSM technique simulates the conditions of a randomized experiment by relying on two assumptions. The first is the assumption of conditional independence (or unconfoundedness) which requires potential outcomes to be independent of

treatment, conditional on background variables. Under the conditional independence assumption, the propensity score is defined as the conditional probability of receiving treatment, given pre-treatment characteristics:

$$p(X) = pr(T = 1|X) \quad (2)$$

For our purposes, the conditional assumption implies that by adjusting for all observable covariates (or 'pretreatment' differences) between food secure and food insecure households, we can regard the treatment assignment, food security, as random and uncorrelated with the conflict outcome. The second assumption of PSM is the common support assumption which states that for each value of X, there is a positive probability of being both treated and untreated, i.e.

$$0 < pr\,(T = 1|X) < 1 \quad (3)$$

In other words, it assumes that the support of the conditional distribution of the covariates for food secure households sufficiently overlaps with the conditional distribution of the covariates for food insecure households. If these two assumptions hold, then the PSM estimator for ATT is the mean difference in conflict status between food secure households matched with food insecure households based on their propensity scores. This can be expressed as:

$$ATT = E(Y_1|\, T = 1,\ p(X)) - E(Y_0|T = 1,\ p(X)) \quad (4)$$

Next, we test for the evidence of heterogeneity in the treatment effect by observable characteristics (Crump et al., 2008; Imbens & Woolridge, 2009). Specifically, by employing heterogeneous treatment effect estimation, we test whether food secure households that are benevolent towards others experience a further reduction in conflict. This is achieved by dividing the full sample into two subsamples based on whether the household is benevolent and estimating two separate ATTs for each subsample. The difference of the subsample ATTs provides the heterogenous treatment effects (see Kibriya, Zhang & Xu, 2017; Xie, Brand, & Jann, 2012; Verhofstadt & Maertens, 2014) and is expressed as follows:

$$ATT_{diff} = E[(Y_1 - Y_0)|\, T = 1, B = 1)] - E[(Y_1 - Y_0)|\, T = 1, B = 0)] \quad (5)$$

where B=1 if the household shows benevolence towards others and 0 otherwise.

(c) *Choice of estimation models*

Propensity scores can be calculated using a logit or probit estimation; we use a logit estimation. Once the propensity scores are generated, households must be matched based on their scores. Since PSM methods are sensitive to the exact specification and matching method (Imbens, 2004; Caliendo and Kopeinig, 2008), we employ three commonly used algorithms to ensure the robustness of PSM estimates. These include nearest neighbor matching (NNM), Kernel based matching and radius matching. NNM matches a food secure household to nonfood secure households that are closest to its propensity score. For nearest neighbor matching, we use three nearest neighbors with replacement. This is because replacement increases the quality of matching, especially when there are fewer close matches. Kernel matching uses a weighted average of all non-food secure households to match it with food secure households, placing higher weights on households with similar propensity scores. Following Heckman, Ichimura and Todd (1997), we use the Epanechnikov Kernel function with a bandwidth of 0.06. Radius matching algorithm matches each food secure household with all non-food secure households whose propensity scores fall within the predefined neighborhood of the propensity score of the food secure households (known as the caliper). We choose a caliper of 0.001 which is commonly used in the literature.

The choice of variables included in the estimation is guided both by economic theory and previous research as well as the literature on matching (see Dehejia & Wahba, 2002; Heckman, Ichimura & Todd, 1997, 1998; Abadie & Imbens, 2006; and Caliendo & Kopeinig, 2008). In summary, variable selection for matching methods is an iterative process involving a tradeoff between efficiency and bias. Therefore, it is recommended to start with a rich set of explanatory variables that simultaneously affect treatment and outcome and through a process of iteration selecting the set of covariates that gives the best balance in terms of distribution of propensity scores as well as distribution in covariates across the treated and control groups.

Finally, to ensure the robustness of our estimates, we use a doubly robust estimator (DRE). DRE requires specifying two separate models – one for treatment (food security) and one for the outcome (conflict). The advantage of using a doubly robust estimator is that it allows for

misspecification in either the treatment model or outcome model. That is, as long as either one of the specifications is correct, DRE will provide unbiased estimates. Following Wooldridge (2010), we use the inverse probability weighting regression-adjustment (IPWRA) combination as the DRE. IPWRA estimators use weighted regression coefficients to compute averages of treatment-level predicted outcomes, where the weights are the estimated inverse probabilities of treatment. The contrasts of these averages estimate the treatment effects.

5. RESULTS AND DISCUSSION

(a) Determinants of household food security

Table 3 presents the results from the logit model to determine the likelihood of being food secure, given observable characteristics of the household. The logit model has a pseudo R^2 of 0.18 and correctly predicts the food security status of the sample households 71% of the time.

Overall, the following variables are significant in explaining the likelihood that a household is food secure: the highest level of education attained by the household, household income, access to technology, access to basic services such as drinking water and cooking fuel, access to agricultural extension services, holding a position of power or authority in the community and inhabiting certain areas. Jointly, the variables are significant at 1% level in explaining the probability of being food secure.

The results show that the household education positively affects the probability of the household being food secure. Assuming sufficient flow of information between members of the same household, it is expected that the highest level of education attained by any member of the household will make the household more knowledgeable overall. Education can increase food security by allowing a household to make informed decisions about agricultural practices such as crop diversification or technology adoption which in turn may enhance agricultural productivity.

The table also shows that household income affects food security positively. This is not surprising since financial security equals greater purchasing power. Not only is a financially secure household able to buy more food, it can also invest more in agriculture, thereby increasing production and food security.

Access to technologies such as mobile phones, radios, television, bicycle and motorized vehicles increases the likelihood of being food secure. Increased access to information and communication technologies may reduce information asymmetry as well as transaction cost for farmers, thereby making them more food secure.

Having access to basic services such as safe drinking water and cooking fuel also increases the probability of being food secure. Given that a large fraction of rural households use fuelwood for cooking, it would explain why access to cooking fuel may affect food security. Furthermore, access to agricultural extension services increases the likelihood of being food secure. Farming households that receive extension services from government or non-government organization workers may be more aware of new technologies and ways to use them to increase income and production.

Local leadership and households with members who have held positions of authority in the community make a household more likely to be food secure. Holding important positions in the community can help farmers gain access to credit and other agricultural services via increased social capital. Finally, certain village specific effects appear to positively influence the probability of being food secure. To save space, the details of the villages have been excluded from the table. It may well be that these are regions associated with higher overall production.

Table 3. *Logit estimates of the determinants of household food security*

Variable	Coefficient	Standard error	Marginal effect
Dependent variable: =1 if household is food secure =0 otherwise			
Household size	-0.024	(0.031)	-0.007
Number of adult males	0.013	(0.061)	0.003
Education	-0.052	(0.0404)	-0.012
Education squared	0.006**	(0.002)	0.001
Household income (`000 CDF/capita)	0.004**	(0.001)	0.000
Respondent has written land claim	-0.057	(0.131)	-0.014
Access to technology and markets (yes=1)	0.644***	(0.151)	0.154
Lack of extension services (yes=1)	-0.433***	(0.139)	-0.103
Cooperative membership (yes=1)	-0.024	(0.148)	-0.006
Access to safe drinking water (yes=1)	0.243*	(0.134)	0.058
Inadequate access to cooking fuel (yes=1)	-0.456***	(0.127)	-0.109
Leadership position (yes=1)	0.826***	(0.257)	0.197
Constant	-2.261***	(0.491)	
Village fixed effects	Yes		
Religion controls	Yes		
Summary Statistics			
Pseudo R^2	0.18		
LR chi-square (36)	395.090***		
Log-likelihood ratio	-894.610		
Percentage correctly predicted	70.53%		
Number of observations	1,605		

Source: Authors' calculations based on the survey data.
Note: *, **, and *** indicate significance at 10%, 5% and 1% levels respectively. Village and religion controls have been omitted from the table to save space.

(b) *Impact of food security on conflict*

(i) *Propensity score matching results*

Figure 2 shows the distribution of propensity scores between food secure and food insecure households. A simple visual analysis of the density distributions of propensity scores for the two groups of households shows that there is almost perfect overlap between the estimated scores. Thus, the common support assumption is satisfied. Furthermore, there is sufficient

difference in the distribution of propensity scores between food secure and food insecure households to justify using a matching technique for estimation. Figure 7 in the Appendix also shows the box plots for the propensity score distributions.

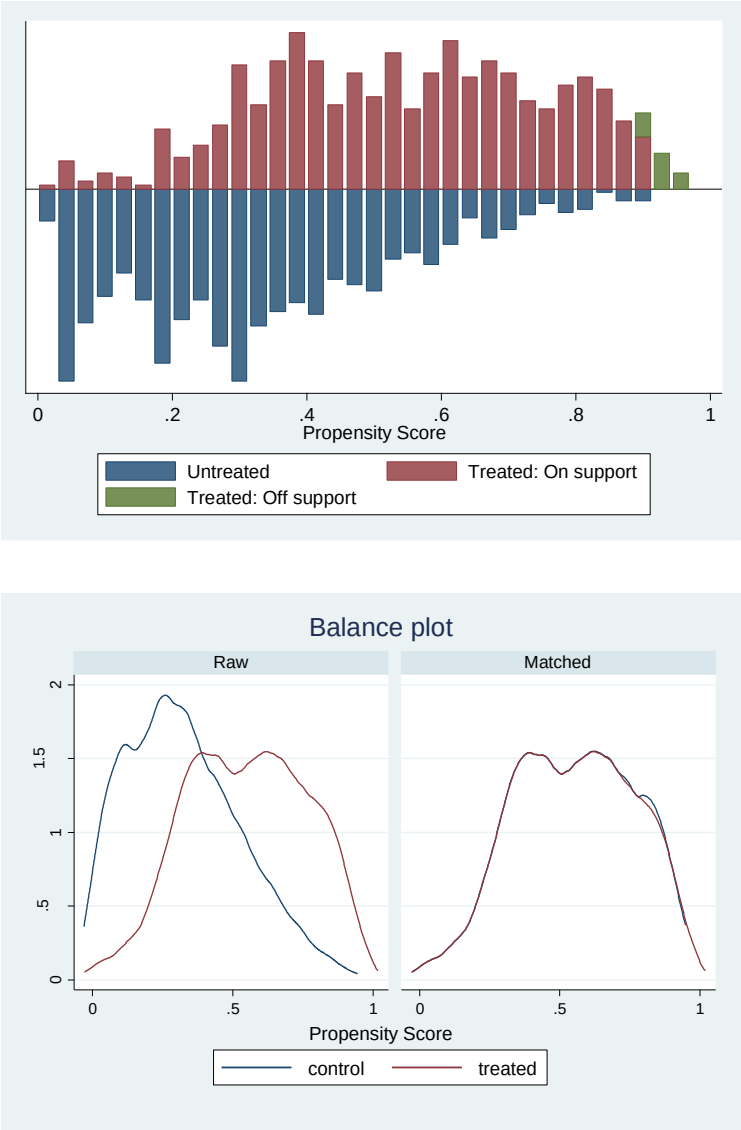

Figure 2. *Distribution of propensity scores and the region of common support. Note: Treated on support indicates households in the food secure group that find a suitable match while treated off support indicates households that do not find a match in the food insecure group. Untreated refers to households that are not food secure.*

The propensity scores for all households range from 0.016 to 0.967 with a mean value of about 0.420 and a standard deviation of 0.233. Food secure households have propensity scores ranging between 0.024 and 0.967 with a mean score of 0.550 and standard deviation of 0.211; while food insecure households have propensity scores ranging between 0.016 and 0.899 with a mean of 0.326 and standard deviation of 0.200. Thus, the region of common support as dictated by the minima and maxima criteria lies between 0.024 and 0.899. About 8.7% of households whose propensity scores fell outside this range were dropped from our analysis.

As a test of the unconfoundedness assumption, we ran a 'Placebo' regression of our treatment variable and all controls on an exogenous dependent variable that is not likely to be related to the treatment. The dependent variable we chose is an indicator variable with value one if the spouse of the household head inherits his land and 0 otherwise. The result shown in Table 9Table *9.* Estimation results from the placebo regression. in the Appendix reveals that the coefficient associated with food security is not significant. While this is not proof that the unconfoundedness assumption holds, since the coefficient on our treatment variable is not significantly different from zero, we cannot reject the null hypothesis of unconfoundedness. This suggests that there are no omitted variables correlated with being food secure and validates our assumption on selection of observables.

Table 4 presents the results of covariate balance test for the matching process. As seen from the table, the means of the treated and control groups are significantly different for most covariates prior to matching. The matching process reduces the difference in means between treated and control groups for all covariates such that there are no significant differences between the means of the two groups after matching.

In addition, we test the percentage bias in means between the treated and control groups post matching. Following Rubin (2001), we consider a covariate to be balanced across treated and control groups if the absolute percent standardized difference in mean bias in the matched sample is 25% or less. Table 4 shows that the absolute percent standardized difference in mean

bias between treated and control groups is indeed less than 25% for all covariates in the matched sample. Since 25% is a rule of thumb, it is assuring to find that the absolute percentage bias in all our covariates is in fact less than 12%. These figures ensure us that the balancing property is satisfied for all covariates of interest.

Table 4. *Balancing properties of covariates before and after matching*

		Mean				
Covariate	Sample	Treated	Control	% Bias	% Reduction in bias	Diff: *p*-value
Household size	U	5.45	5.23	9.1		**0.058**
	M	5.33	5.30	1.3	85.5	0.834
Number of adult males	U	2.24	2.10	12.1		**0.011**
	M	2.15	2.23	-6.8	44.3	0.293
Household education	U	9.50	8.83	14.6		**0.004**
	M	9.15	9.54	-8.3	43.3	0.214
Household education squared	U	111.90	99.42	15.5		**0.002**
	M	106.10	115.42	-11.6	25.3	0.095
Household income	U	19583	16370	8.1		0.101
	M	20235	20009	0.6	93	0.943
Written claim of land (yes=1)	U	0.37	0.43	-11		**0.023**
	M	0.4	0.42	-4.4	60.3	0.495
Access to technology and markets (yes=1)	U	0.83	0.69	34.7		**0**
	M	0.80	0.82	-6.3	81.9	0.294
Lack of extension services (yes=1)	U	0.59	0.62	-6.6		0.169
	M	0.60	0.59	1.9	71.9	0.772
Cooperative membership (yes=1)	U	0.22	0.21	4.5		0.35
	M	0.23	0.24	-0.1	97.6	0.987
Access to safe drinking water (yes=1)	U	0.63	0.63	1.1		0.817
	M	0.65	0.66	-3.1	-172.2	0.626
Inadequate access to cooking fuel (yes=1)	U	0.56	0.64	-16.8		**0.001**
	M	0.58	0.56	4	76	0.536
Leadership position (yes=1)	U	0.96	0.91	18.6		**0**
	M	0.94	0.96	-5.4	71.1	0.335

Source: Authors' calculations based on the survey data.

Note: U=unmatched sample and M=matched sample. For each covariate, the standardized mean percent reduction in bias is calculated using one minus the difference in means between treated and control groups after matching divided by the difference in means between treated and control groups before matching. Bold p-values indicate the difference in means are significant at a level of 10% or lower. Due to space constraints, the means for village and religion dummies have been excluded from the table. The number of observations is 675 for treated and 930 for control groups. The balancing tests presented here are for the onset of conflict outcome using radius-caliper matching. The results are similar for other outcomes and for the other matching algorithms used. Therefore, to save space those are not reported.

(ii) *Average treatment effect on the treated*

Table 5 summarizes the ATT estimates of food security on household conflict for the different matching algorithms. Consistent across all methods, we find that food security reduces the probability that a household experiences conflict. Overall, households that are food secure are less likely to engage in conflict on average and are expected to experience fewer types of conflicts than they would have had they not been food secure. The coefficients and significance values are similar across the different matching methods. On average, food secure households are approximately 10 percentage points less likely to experience conflict than they would have been had they not been food secure.

Table 5. *Average treatment effect of food security on conflict*

Outcome Variable	Treatment variable: food security		
	Nearest-neighbor (3)	Kernel matching	Radius matching
Probability of conflict	-0.095***	-0.101***	-0.099 ***
	(0.027)	(0.030)	(0.042)
Probability of conflict with individual households	-0.089***	-0.095 ***	-0.100***
	(0.0271)	(0.033)	(0.046)
Probability of conflict with groups	-0.040*	-0.033*	-0.033*
	(0.023)	(0.018)	(0.030)
Types of conflict incurred	-0.310***	-0.300***	-0.329***
	(0.059)	(0.085)	(0.091)

Source: Authors' calculations based on the survey data.
Note: *, **, and *** indicate significance at 10%, 5% and 1% levels respectively. All estimates shows are average treatment effect on the treated. Abadie and Imbens (2006) robust standard errors reported for nearest neighbor matching while bootstrapped standard errors with 100 replications of the sample are reported for kernel and radius matching. Kernel matching uses a bandwidth of 0.06 while radius matching uses a caliper of 0.001. Number of observations=1605 for all matching algorithms.

Disaggregating by conflict type, we find that food security reduces the probability that a household will engage in conflict with other households by about 9 to 10 percentage points. The probability of food secure households engaging in conflict with the community reduces by 3 to 4 percentage points compared to the likelihood of conflict had the household not been food secure. Finally, food secure households experience 30% to 33% fewer types of conflict on average than food insecure households. While most of the coefficients are significant at 1% level or less, the

coefficients on conflict with the community is significant only at 10% or less. This may have been driven by the relatively fewer number of observations in this category.

These results support our expectation that controlling for socioeconomic differences, food secure households experience lower levels of conflict with other households and with groups within the community. Food security reduces cause for grievance and general frustrations which can translate to more aggressive and anti-social behavior in society. Households that do not have to worry about food may be less prone to incentives to join a rebellion. In addition, there is a cost associated with engaging in conflict and food secure households have fewer incentives to be willing to incur the cost.

Table 6 compares the performance of the three matching algorithms used. For all three matching techniques used, the standardized mean bias for covariates overall reduced from 14.0 before matching to a range between 2.7 and 3.9 after matching; while the total percentage bias reduced by around 78 to 82 percent. The p-values of the likelihood ratio tests show the joint significance of all covariates in the logit regression after matching.

Table 6. *Comparing matching quality indicators among the three matching algorithms*

Matching algorithm	Pseudo R^2		LR χ^2		$p > \chi^2$		Mean standardized bias		Total % bias reduction
	Before	After	Before	After	Before	After	Before	After	
NNM	0.180	0.010	392.97	19.26	0.000	0.990	14.0	3.2	77.9
EKM	0.180	0.007	392.97	12.17	0.000	1.000	14.0	2.7	82.3
RM	0.180	0.012	392.97	16.96	0.000	0.997	14.0	3.9	75.3

Source: Authors' own calculations using the survey data.
Note: NNM=nearest neighbor matching using three nearest neighbors with replacement. EKM= Epanechnikov kernel matching with a bandwidth of 0.06. RM=radius matching using a caliper of 0.001. Before and after refer to results before matching and after matching.

The low values of the pseudo R^2 after matching indicate that there is no systematic difference in the distribution of the treated and control groups. Overall, the low pseudo R^2, the

high p-values and the reduction in bias post matching assure us that the propensity score matching has successfully balanced the distribution of covariates in treated and control groups. Although the values are similar for all three methods used, the performance was slightly better for kernel based matching.

(c) The heterogenous effect of food security conditional on benevolence

Having established that food security reduces conflict at the household and community level, we further our investigation to test for the presence of heterogenous effects of the treatment. In particular, we test whether conditional on benevolence household food security can reduce conflict even further.

To do this we subsample the data into households that show benevolence towards others by helping them with food, and households that do not. For each subsample, we estimate the ATT and compare results. Table 7 shows the results from the propensity score estimation. What is immediately obvious from panel A across all estimation techniques is that conditional on benevolence, food security reduces conflict for the average household in a statistically significant way.

When the household is not benevolent, the impact of food security on conflict diminishes in magnitude but is statistically insignificant in most cases. On average food security reduces the probability that a benevolent household will experience any kind of conflict with others by 8 to 13.8 percentage points; conflict with individual households by 8.3 to 12.4 percentage points; and conflict with groups or the community by 2.6 to 5.3 percentage points. Food security also reduces the average number of types of conflict the household experiences by 24.4% to 38%.

Table 7. *Effect of food security conditional upon benevolence of household*

Outcome Variable	Matching Algorithm		
	NNM (3)	KM	RM
Panel A: Effect of food security given household is benevolent			
Probability of conflict	-0.106**	-0.138***	-0.080*
	(0.045)	(0.042)	(0.046)
Probability of conflict with individual households	-0.110**	-0.124***	-0.083*
	(0.045)	(0.042)	(0.045)
Probability of conflict with groups	-0.036*	-0.053*	-0.026*
	(0.032)	(0.030)	(0.031)
Types of conflict incurred	-0.329***	-0.380***	-0.244***
	(0.110)	(0.104)	(0.112)
Number of Treated	521	521	298
Number of Controls	585	585	585
Panel B: Effect of food security given household is not benevolent			
Probability of conflict	-0.019	-0.025	0.139
	(0.067)	(0.061)	(0.088)
Probability of conflict with individual households	-0.019	-0.019	0.136
	(0.068)	(0.061)	(0.088)
Probability of conflict with groups	-0.060	-0.052	-0.058
	(-0.060)	(0.046)	(0.060)
Types of conflict incurred	-0.176	-0.177	0.200
	(0.182)	(0.159)	(0.193)
Number of Treated	144	143	63
Number of Controls	315	315	315

Source: Authors' own calculations based on survey data.
Note: All coefficients reported show average treatment effect on the treated. Robust standard errors in parenthesis. *, **, and *** denote significance at or below 1%, 5%, and 10% levels. Number of treated refer to the number of treated that fall in the region of common support. NNM=nearest neighbor matching using three nearest neighbors with replacement. EKM=Epanechnikov kernel matching with a bandwidth of 0.06. RM=radius matching using a caliper of 0.001. IPW-RA= inverse probability weighted regression analysis.

Furthermore, as hypothesized, the conditional impact of food security on conflict given the household is benevolent is even larger than the unconditional effect of food security on conflict. For example, comparing the results from the kernel estimation in Table 7 to those in Table 6 shows that while the unconditional impact of food security on overall conflict is 10.1 percentage point reduction, the conditional impact is a 13.8 percentage point reduction. This means the

probability of conflict reduces a further 3.8 percentage points given the household is benevolent. Similarly, the reduction in conflict with individuals and conflict with groups reduces by 12.4 and 5.3 percentage points, respectively, compared to a 9.5 and 3.3 percentage point reduction, respectively, for the unconditional impact. Finally, a food secure household that shows benevolence can expect up to a 38 percentage point further reduction in conflict compared to a food insecure household.

These results support our hypothesis that food secure households that show benevolence towards others by helping them with food have a lower propensity of being involved in situations of conflict. By helping others, benevolent households may gain popularity and respect and thus help establish stronger social ties within the community. This may even discourage violent parties from aggravating these households. Benevolent households may also be able to avoid altercations by providing food to rebel groups or violent subgroups within the community. Supporting others in times of crises can impart a sense of trust and goodwill among households, leading to greater social cohesion and reduced conflict in society.

The covariate balance test for the matching process is shown in Table 10 for benevolent households and Table 11 for non-benevolent households. The means of the treated and control groups are significantly different for most covariates prior to matching. The matching process reduces the difference in means between treated and control groups for all covariates such that there are no significant differences between the means of the two groups after matching. Table 12 in the Appendix shows results for the various matching quality indicators in the two subsamples. Overall, the indicators perform better after matching, thereby ensuring the quality of the matching process in both the subsamples.

(d) Sensitivity Analysis

Table 8 presents the results from the doubly robust estimation procedure using the inverse probability weighted regression analysis (IPWRA). The doubly robust estimates of the average treatment effects of being food secure are very similar to the results from the matching

algorithms in Table 5. On average, food security reduces the likelihood that a household experiences conflict by about 10 percentage points for conflict overall, 9.5 percentage points for conflict with other households and 3.6 percentage points for conflict with groups within the community. On average, food secure households are likely to experience 31% fewer types of conflict compared to their food insecure counterparts. The similarity in results from the doubly robust estimation and propensity score matching assures us of reliable estimates.

The doubly robust estimation from the impact of food security given benevolence is shown in the fourth column. Two important notes can be made from the results. First, the estimates are similar to the propensity score estimates shown in Table 7. Second, comparing the doubly robust estimates of food security conditional on household benevolence to the unconditional impact of food security on conflict once again demonstrates that the conditional estimates are larger in absolute value. This result further substantiates our hypothesis that food secure households that show benevolence towards others in society by helping them with food experience a further reduction in conflict both at the individual household and community level.

Table 8. *Doubly robust estimation and Rosenbaum critical level of hidden bias results*

Outcome Variable	Treatment: food security		Treatment: food security given benevolence	
	IPWRA	Critical level of hidden bias (Γ)	IPWRA	Critical level of hidden bias (Γ)
Probability of conflict	-0.101***		-0.138***	
	(0.031)	5.50	(0.033)	2.05
Probability of conflict with individual households	-0.095***		-0.024***	
	(0.031)	1.65	(0 .033)	1.65
Probability of conflict with groups	-0.0360*		-0.053*	
	(0.020)	3.25	(0 .025)	3.65
Types of conflict incurred	-0.308***		-0.380***	
	(0.067)	1.85	(0.115)	2.20
Number of observations	1605		1106	

Source: Authors' calculations based on the survey data.

Note: *, **, and *** indicate significance at 10%, 5% and 1% levels respectively. IPWRA refers to inverse probability weighted regression analysis. AI robust standard reported. Critical level of hidden bias (Γ) refers to the Rosenbaum bounds for hidden bias using Hodges-Lehmann point estimates. Critical level results refer to propensity score matching using kernel estimation. Results from other matching methods are similar and omitted to save space.

Finally, we test the sensitivity of our estimates using the Rosenbaum bounds for hidden bias (Rosenbaum, 2002). Since PSM matches households based only on observable covariates, potential bias in estimates may arise from selection on unobservables. For example, if household members are aggressive in nature, both in pursuing measures to make themselves food secure as well as in their attitude towards violence, our estimates may be biased. The Rosenbaum bound (Γ) measures how big the difference in unobservables need to be to in order to make ATT estimates insignificant. We use the Hodges-Lehmann point estimates.

We find that under the assumption of no potential hidden bias, i.e. when $\Gamma = 1$, the results are similar to our estimates. With food security as the treatment, the values of Γ range between 1.65 and 5.5. This implies that the unobserved covariates would have to increase the odds of being food secure by a factor of 1.65 (65%) to 5.5 (450%) to overturn the significance of our ATT estimates. When the treatment is food security conditional on benevolence, Γ ranges between 1.65 and 3.65. This implies that matched households with the same observed covariates would have to differ by a factor of 1.65 (65%) to 3.65 (265%) to render our ATT estimates insignificant. Based on these results we can conclude that our findings are robust to potential hidden bias from unobserved covariates.

6. CONCLUDING REMARKS AND POLICY IMPLICATIONS

By exploiting survey data of 1763 farming households collected from three territories in the North Kivu province of eastern DRC, we study the impact of food security on low intensity local conflict at the household level. Since food secure households may be systematically different from food insecure households, we use the quasi-experimental method of propensity score matching to control for any preexisting differences. By using various techniques to match food secure households to food insecure households that are similar in every way except for their food security status, we can successfully isolate the causal effect of food security on household conflict. We find evidence that food security reduces the overall probability of conflict experienced by a typical household by as much as 10 percentage points. By disaggregating

conflict by types, we further show that a food secure household will on average have an 8.9 to 10 percentage point lower probability of engaging in conflict with other individual households in the community. In contrast, food security reduces the probability that a household will experience conflict with groups, such as government and rebel forces or communal conflict over public resources, by 3.3 to 4 percentage points. Additionally, food secure households face between 30% and 35% fewer types of conflict on average than food insecure households. Finally, by exploiting heterogenous treatment effects we show that food security can reduce the probability of conflict even further for households that show benevolence towards others in the community by helping them with food. More specifically, food secure households that show benevolence towards others can face a reduction of up to 13.8 percentage points in the overall probability of conflict; a reduction of up to 24 percentage points in the probability of conflict against individual households and a maximum reduction of 5.3 percentage points in the probability of conflict against groups within the community. In addition, food secure households that are also benevolent are faced with 38% fewer types of conflict.

The empirical evidence supports our initial hypothesis that food security reduces a household's propensity to experience conflict with other households and with groups within the community. Furthermore, benevolence may be a potential channel through which food security can reduce household conflict. By assisting others with food, benevolent households gain the respect of fellow community members. Supporting others in times of crises can impart a sense of trust and goodwill among households, leading to greater social cohesion and reduced conflict in society. In addition, violent members within the community may avoid confrontations with such households. Finally, benevolent households may themselves be able to avoid conflict with violent parties such as rebel groups by offering them food and mediating potential conflict.

Potential biases were accounted for through various econometric approaches. The assumption of selection on observables is addressed through a placebo regression, while the overlap assumption is assessed through normalized differences in means and graphical representation of propensity score distributions. The inverse probability weighted regression analysis is used as a doubly robust estimator to check the robustness of our estimates. Finally, the Rosenbaum bounds for hidden bias is used to test the sensitivity of our analyses to any potential

bias arising from unobservable confounders. The results from all these checks and balances ensure us that our findings are robust. Although we take extreme caution to claim causality between the complex relationship of food security and communal conflict, our results show no concern for the assumptions used, suggesting that a causal claim of our finding is plausible.

Our approach of analyzing the connection between hunger and conflict is novel. While the existing literature explores the connection between hunger and conflict and mostly uses cross country or district level data for macro level analyses of civil wars and conflicts, we were able to use household level information. Our research also distinguishes itself by offering to investigate a more policy oriented question. While the existing evidence linking hunger and conflict is helpful, it does not prove that food security can lead to stability and peace at a household level. Our results provide evidence that the promotion of food security in rural households in violence prone areas can enhance peace and stability. In addition, we find evidence that food security can further reduce conflict through community cohesion and benevolent approaches.

Our findings advance the understanding of the intricate relationship between conflict and hunger at the micro-level and add to the new wave of action-oriented research. Food aid programs have been documented to have mixed effects on conflict (Barret, 2001; Nunn & Qian, 2014; WFP, 2009b; UN PBSO, 2010). In light of our analysis, we encourage policy makers to design development projects that would emphasize building household level food security to reduce communal conflict. It also appears that trust-building initiatives within the community can help build social capital and cohesion within the community that could help control violent behavior and animosity at the local level before it leads to large scale conflict. Such programs should be inclusive and ensure that individual households are empowered as opposed to privileged groups. In the context of North Kivu, DRC, such programs are necessary to mitigate the adverse effects of a long history of conflict resources and to avoid another set of mass genocide.

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APPENDIX

Table 9. *Estimation results from the placebo regression.*

Dependent variable: spouse of interviewee inherits land	Coefficient	Standard error
Food secure	0.018	0.022
Household size	0.001	0.005
Number of adult males	-0.006	0.010
Number of adult males	0.016**	0.007
Highest level of education squared	-0.001***	0.003
Household education	-5.27e-07**	2.68e-07
Has written claim of land	0.020	0.023
Household education squared	0.004	0.026
No service	-0.070***	0.023
Household income	-0.008	0.025
Access to drinking water	-0.053**	0.022
Written claim of land (yes=1)	-0.041*	0.022
Power	0.219***	0.040
Constant	0.364***	0.084
Observations	1,537	
R-squared	0.181	
Groupement and Religion Dummies	Yes	

Source: Authors' own calculations.
Note: *, **, and *** indicate significance at 10%, 5% and 1% levels respectively.

Table 10. *Covariate balance in treated and control groups for benevolent households*

Covariate	Sample	Treated	Control	% Reduction in bias	Diff: *p*-value
Household size	U	5.50	5.18		**0.027**
	M	5.53	5.50	89.7	0.836
Number of adult males	U	2.24	2.14		0.148
	M	2.25	2.31	38.6	0.422
Household education	U	9.73	9.38		0.194
	M	9.73	9.55	46	0.501
Household education squared	U	114.84	107.01		0.099
	M	115.06	110.51	41.8	0.38
Household income	U	19553	15483		0.05
	M	19716	27362	-87.9	0.127
Written claim of land (yes=1)	U	0.39	0.48		**0.004**
	M	0.40	0.41	78.2	0.556
Access to technology and markets (yes=1)	U	0.86	0.76		**0**
	M	0.86	0.86	98	0.929
Lack of extension services (yes=1)	U	0.57	0.60		0.318
	M	0.55	0.58	22.8	0.472
Cooperative membership (yes=1)	U	0.26	0.23		**0.2**
	M	0.26	0.25	60.6	0.642
Access to safe drinking water (yes=1)	U	0.63	0.64		0.695
	M	0.63	0.62	74.9	0.927
Inadequate access to cooking fuel (yes=1)	U	0.57	0.65		**0.003**
	M	0.58	0.53	35	0.077
Leadership position (yes=1)	U	0.97	0.90		**0**
	M	0.97	0.97	96.2	0.802

Source: Authors' calculations based on the survey data.

Note: U=unmatched sample and M=matched sample. For each covariate, the standardized mean percent reduction in bias is calculated using one minus the difference in means between treated and control groups after matching divided by the difference in means between treated and control groups before matching. Bold p-values indicate the difference in means are significant at a level of 10% or lower. Due to space constraints, the means for village and religion dummies have been excluded from the table. The number of observations is 675 for treated and 930 for control groups. The balancing tests presented here are for the onset of conflict outcome using radius-caliper matching. The results are similar for other outcomes and for the other matching algorithms used. Therefore, to save space those are not reported. N=1054

Table 11. *Covariate balance in treated and control groups for non-benevolent households*

Covariate	Sample	Treated	Control	% Reduction in bias	Diff: *p*-value
Household size	U	5.27	5.32		0.772
	M	5.14	5.25	-87.5	0.673
Number of adult males	U	2.27	2.03		**0.015**
	M	2.27	2.33	73.2	0.640
Household education	U	8.83	7.92		**0.062**
	M	8.79	8.79	99.8	0.997
Household education squared	U	103.33	86.99		**0.043**
	M	103.35	101.89	91	0.887
Household income	U	19886	17761		0.656
	M	20208	23647	-61.9	0.662
Written claim of land (yes=1)	U	0.30	0.35		0.327
	M	0.31	0.34	45.4	0.669
Access to technology and markets (yes=1)	U	0.78	0.57		**0.000**
	M	0.76	0.76	97.6	0.920
Lack of extension services (yes=1)	U	0.65	0.66		0.803
	M	0.65	0.66	53.3	0.926
Cooperative membership (yes=1)	U	0.10	0.17		**0.044**
	M	0.10	0.10	99.8	0.996
Access to safe drinking water (yes=1)	U	0.63	0.61		0.651
	M	0.67	0.68	53.4	0.862
Inadequate access to cooking fuel (yes=1)	U	0.56	0.65		0.068
	M	0.57	0.53	48.5	0.464
Leadership position (yes=1)	U	0.91	0.93		0.474
	M	0.93	0.92	62.9	0.832

Source: Authors' calculations based on the survey data.
Note: U=unmatched sample and M=matched sample. For each covariate, the standardized mean percent reduction in bias is calculated using one minus the difference in means between treated and control groups after matching divided by the difference in means between treated and control groups before matching. Bold p-values indicate the difference in means are significant at a level of 10% or lower. Due to space constraints, the means for village and religion dummies have been excluded from the table. The number of observations is 675 for treated and 930 for control groups. The balancing tests presented here are for the onset of conflict outcome using radius-caliper matching. The results are similar for other outcomes and for the other matching algorithms used. Therefore, to save space those are not reported. N=459.

Table 12: *Matching quality indicators for benevolent and non-benevolent households*

Sample	Pseudo R^2	LR χ^2	$p > \chi^2$	Mean standardized bias	%Bias	Total % bias reduction
			Panel A: Household is benevolent			
Unmatched	0.197	301.68	0	14.5	112.5*	
Matched	0.013	18.62	0.993	3.7	26.5*	76.4
			Panel B: Household is not benevolent			
Unmatched	0.174	99.62	0	15.1	107.6*	
Matched	0.009	3.5	1	2.8	22.1	79.4

Source: Authors' own calculations using the survey data.
Note: Results shown for Epanechnikov kernel matching with a bandwidth of 0.06. * indicates that %bias is over 25.

Figure 3: Map of DRC showing North Kivu

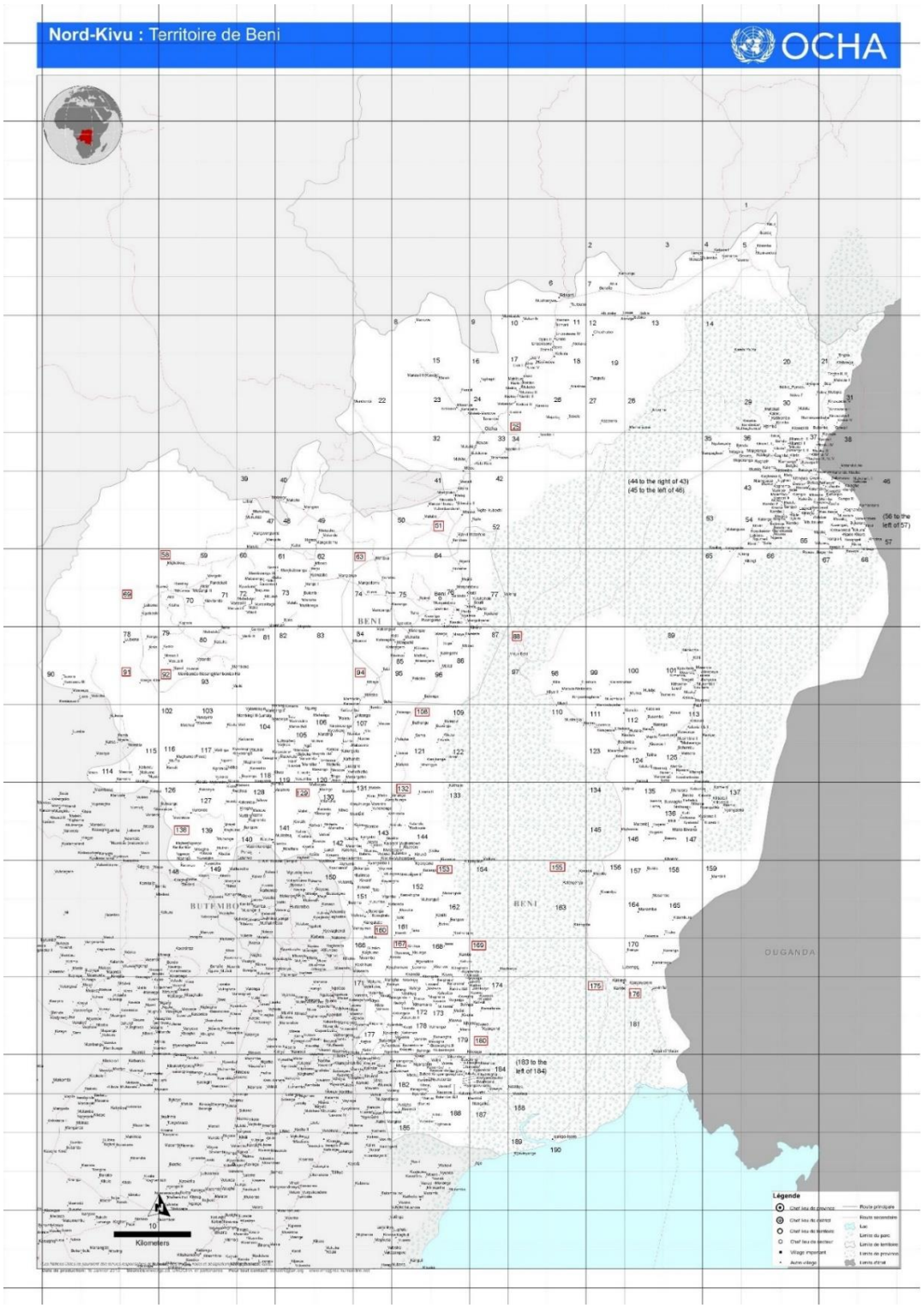

Figure 4: Grid map of Beni territory

Source: The United Nations Office for the Coordination of Humanitarian Affairs *(OCHA), available at* www.rgc.cd

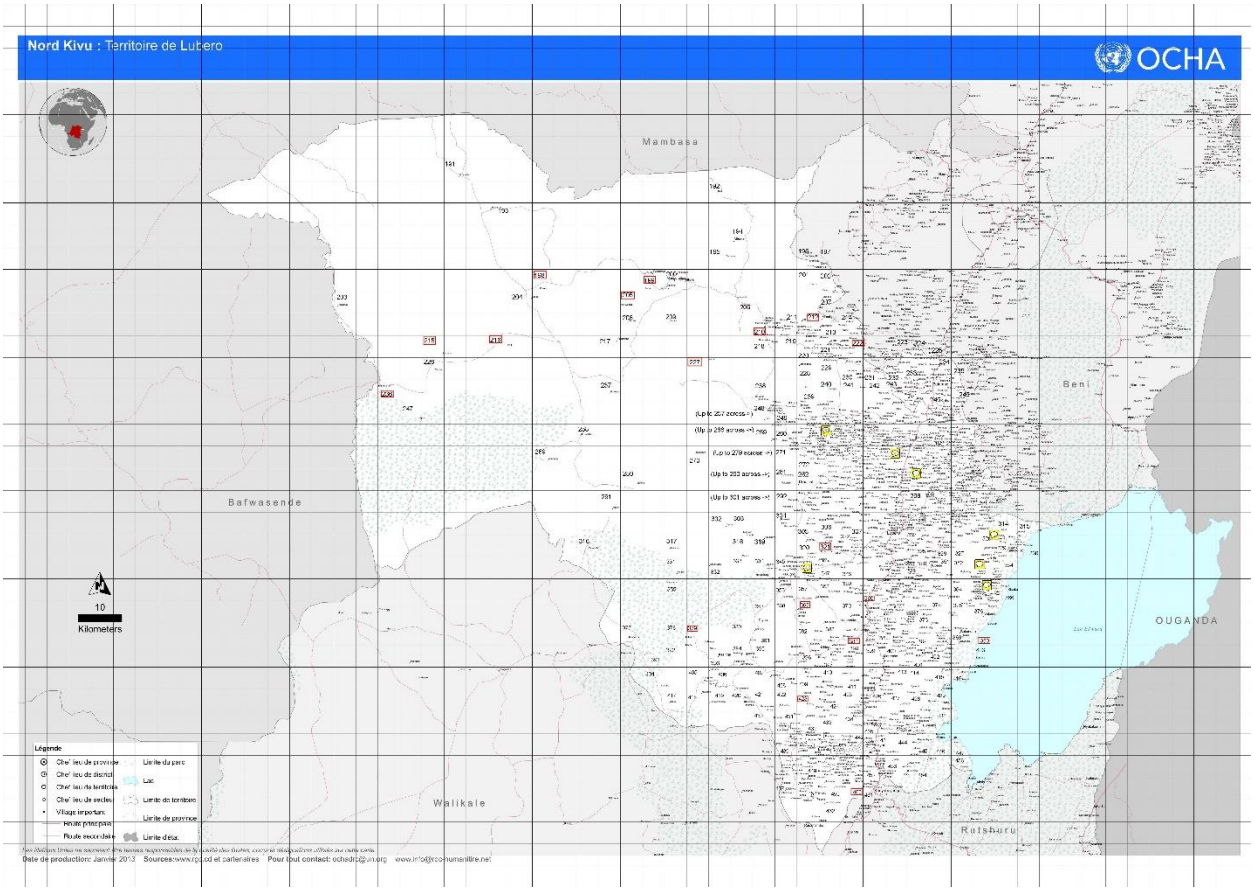

Figure 5:Grid map of Lubero territory

Source: The United Nations Office for the Coordination of Humanitarian Affairs *(OCHA), available at* www.rgc.cd

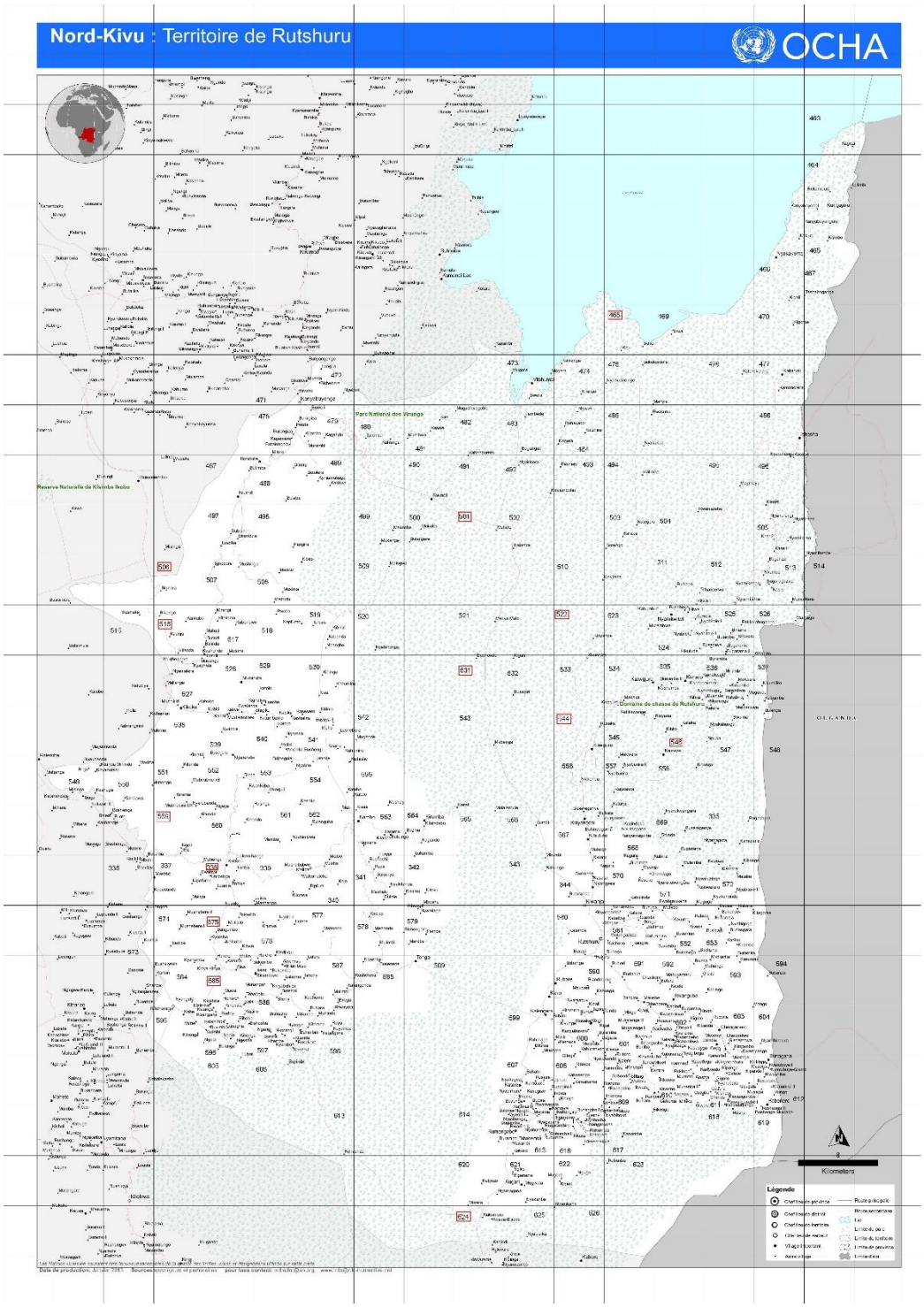

Figure 6: Grid map of Rutshuru territory

Source: The United Nations Office for the Coordination of Humanitarian Affairs *(OCHA), available at* www.rgc.cd

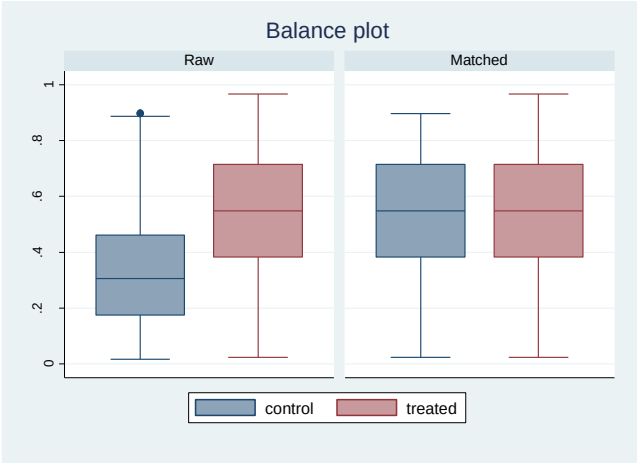

Figure 7: Box plot to show distribution of propensity score between treated and control groups before and after matching

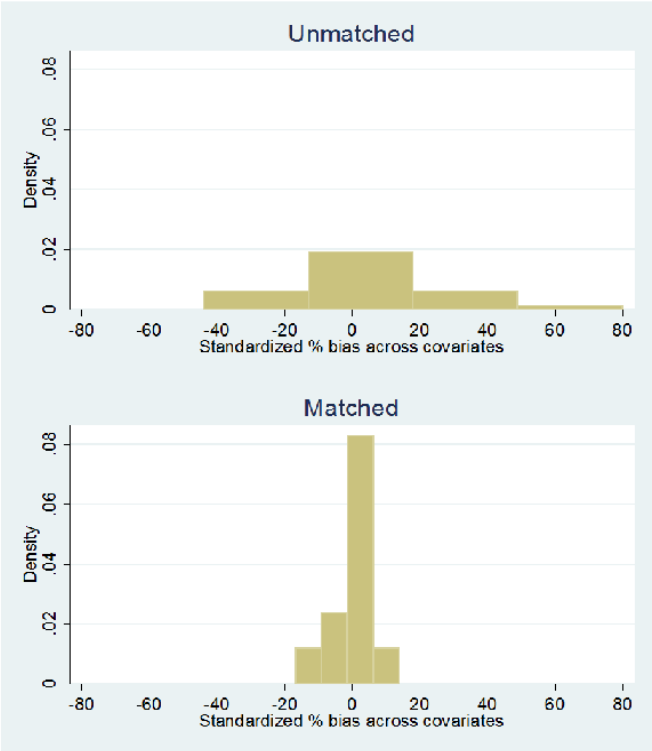

Figure 8:Histogram of standardized differences before and after matching

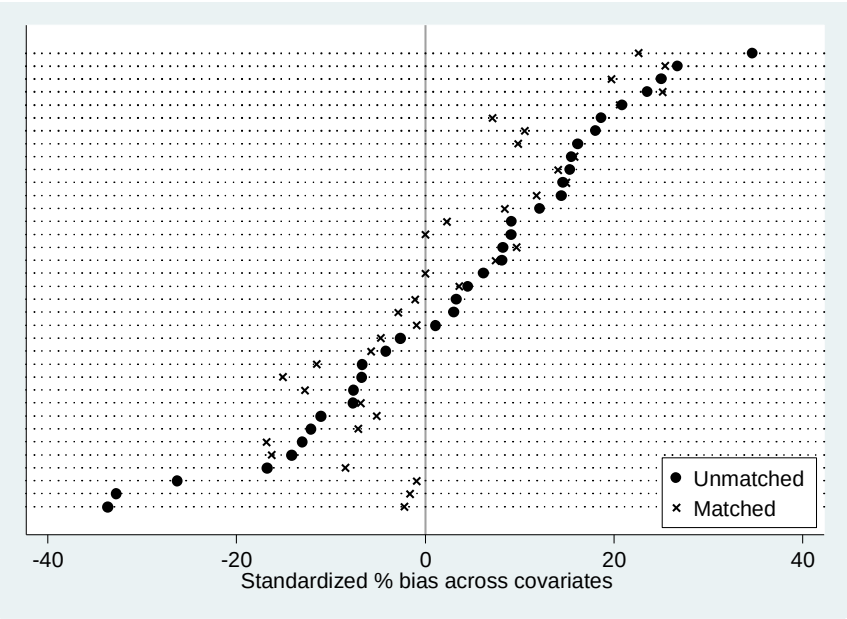

Figure 9: Graph of standardized differences before and after matching

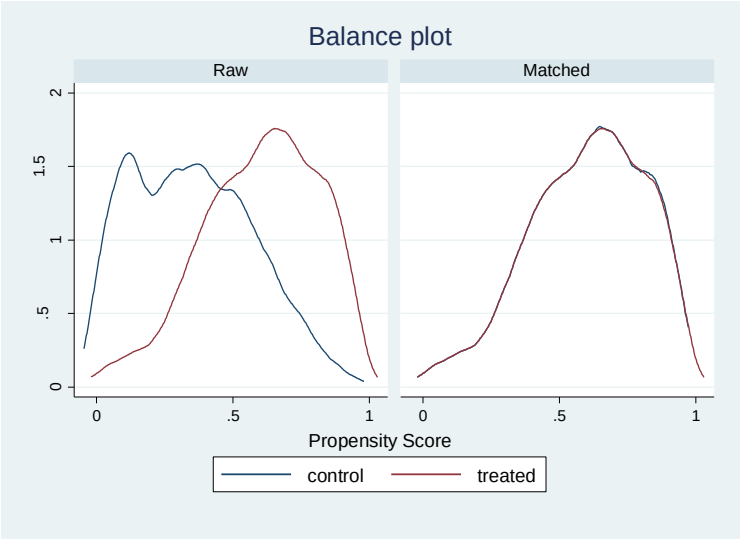

Figure 10: Distribution of propensity scores in unmatched and matched samples for benevolent households

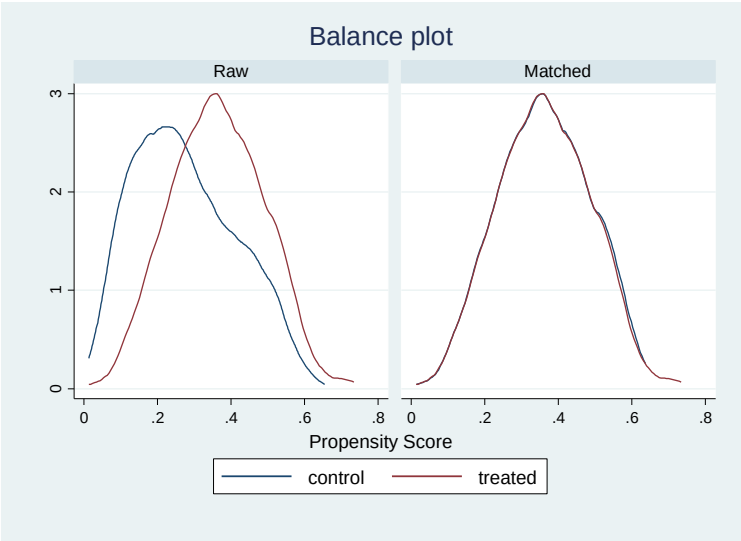

Figure 11:Distribution of propensity scores in unmatched and matched samples for non-benevolent households