H i C N Households in Conflict Network
The Institute of Development Studies - at the University of Sussex - Falmer - Brighton - BN1 9RE
www.hicn.org

Givers of great dinners know few enemies: The impact of household food sufficiency and food sharing on low intensity interhousehold and community conflict in Eastern Democratic Republic of Congo

Naureen Fatema* and Shahriar Kibriya†

HiCN Working Paper 267

March 2018

Abstract: Our study establishes a linkage between household level food sufficiency and food sharing with the reduction of low intensity micro level conflict using primary data from 1763 households of Eastern Democratic Republic of Congo. We collect categorized experiences of household and community level disputes and altercation information, along with food sufficiency and food sharing data from communities of North Kivu. Based on previous academic work we formulate two primary research questions. First, we ask if food sufficient households are less likely to engage in low intensity individual and community level conflict. Next, we ask if there are heterogeneous effects of food sufficiency on interhousehold and community level conflict, conditional on food sharing. Using propensity score matching, we find that household food sufficiency status reduces probability of conflict with other households and groups within the community by an average of around 10 percentage points. However, upon conditioning on food sharing behavior, we find that food sufficient households that share their food reduce their probability of conflict by 13.8 percentage points on average while the effects disappear for households who do not share their food. We conclude that food sufficiency reduces low intensity interhousehold and community conflict only in the presence of such benevolence. Our results hold through a rigorous set of robustness checks including doubly robust estimator, placebo regression, matching quality tests and Rosenbaum bounds for hidden bias. While most literature studies information on violent conflict, our effort focuses on various facets of interhousehold and community conflicts that until now have been mostly unexplored. Our findings show that food sufficiency cannot reduce social altercations unless accompanied by benevolent behavior. As such, our approach can offer new insights to development researchers and practitioners with measuring and studying low intensity household and community conflict.

Key words: Micro-level household and community conflict; household food sufficiency; propensity score matching; North Kivu, DRC; Africa.
JEL Codes: Q 12, O12, Q 18, D 74, D 13

* Department of Economics, McGill University, Canada. Email: naureen.fatema@mail.mcgill.ca
† Center on Conflict and Development, Texas A&M University, USA. Email: shahriar@tamu.edu

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 of violent armed combat. 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). While these studies strongly establish hunger as one of the drivers of violent combat at a national or subnational level, there has been limited research on interpersonal aggression which could provide insights into the behavioral or psychological norms through which food security and micro level low intensity conflict[1] 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 exploring the

[1] In this article we define micro level low intensity conflict as aggressive yet rarely violent behavior at the individual or community level.

link between household level food sufficiency and food sharing (also refereed as benevolence in this article) on interhousehold and community level low intensity conflict with primary survey data collected from 1763 households of Beni, Lubero, and Rutshuru territories of North Kivu, Democratic Republic of Congo (DRC).

Recently, scholars have acknowledged this need for micro level conflict 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) reports that micro-empirical studies typically use crude measure of household conflict - proximity to battle grounds and violence. However, there is a dearth of analysis on more nuanced aspects of conflict that may emerge from collecting and studying micro level incidents of low intensity social altercations experienced by households and communities.

Our conjecture is such micro level incidents can be averted by food sufficient and benevolent households. Accordingly, we investigate two specific questions, i) are food sufficient households less likely to engage in low intensity interhousehold and community level conflict; and ii) are there heterogeneous effects of food sufficiency on interhousehold and community conflict, conditional on food sharing? To successfully answer these research queries, it was important that our contextual region had prevalent food insecurity and different scenarios of low intensity individual and community level conflict. Eastern Democratic Republic of Congo is one such region with these existing socio-political conditions. 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) and with a history of recent civil conflict, low governance and community violence.

We remain circumspect to endogeneity issues and take several precautionary measures in our experimental set up and estimation approaches. Given that food sufficient and food insufficient households may be systematically different, we employ the quasi-experimental estimation technique of propensity score matching (PSM) to estimate the effects of food sufficiency on household and community level conflict. 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 insufficient (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 households that are not food sufficient, and thus a causal interpretation of the results is reasonable (Imbens & Woolridge, 2009).

Our initial set of results show that a household's food sufficiency status reduces its probability of conflict with other households and groups within the community by 10 percentage points. However, upon conditioning on benevolence, we find that in food sufficient households the probability of conflict reduces by around 13.8 percentage points on average while the effects disappear for the non-benevolent households. We conclude that food sufficiency reduces low intensity interhousehold and community conflict only in the presence of benevolence. Although we took measures to control for various sources of bias, we show extreme caution to claim causality. However, at a minimum, our results establish a micro-foundational linkage scarce in the literature.

Our attempt stands to make two unique contributions. First, our initiative documents micro-level information of categorized disputes between neighbors, extended family members, pastoralists, and government and rebel forces which remain largely unreported. Second, to the best of our knowledge, this is the first attempt to empirically examine the effects of having sufficient food, conditional on benevolence, on interhousehold and community conflict.

The remainder of the paper is organized as follows: section 2 describes the context and study justification; 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 Context*

Despite being one of the most resource rich countries in the world, the Democratic Republic of Congo is plagued by food insecurity, inequality and poverty, unstable governments, weak property rights, rebel groups and competition over resources. About 70 percent of the employed population is engaged in agriculture, mostly for subsistence (IFAD, extracted April 2016). 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. Of D.R.C.'s population of 74.88 million, 63.6 percent live below the poverty line and lack access to adequate food while about seven million people are food insecure (WFP 2016).

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, unrest 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.

At present, North Kivu 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). Citizens have a lack of food access, social governance and cohesion that are sowing the seeds of micro level interhousehold and community conflicts. Our field studies show semi and non-violent altercations are common among fellow villagers, government and supporters of rebel groups, pastoralists and famer groups, extended family members and community members at large. Thus, given pervasive hunger, ongoing history of conflict and current social tensions, North Kivu provides an ideal yet unfortunate setting for this study.

(b)   Study justification

Significant research has been reported in interdisciplinary development journals on food security driving conflict. However, studies related to our specific effort is lacking since we approach conflict from a largely non-armed and interpersonal level. Food insecurity has been shown to initiate feelings of horizontal inequality, grievances and discontent (Humphreys & Weinstein, 2008, Qstby, 2008; Stewart, 2011); while even illusions of food security (or such programs) have been noted to provide a comforting sense (White et. al, 2016). Nutrition and health studies also show that lack of food and hunger is related to poor mental health, depression, anger and aggression (Chilton & Sue, 2007; Carter et al., 2011; Bushman et. al., 2014; Heflin et al. 2005). Recent exploration in the development literature by Rojas & Guardiola (2017) show that hunger depresses people's subjective wellbeing. On the other hand, evidence from Nepal and South Sudan suggest that food security can enhance a feeling of equality and harmony at a community level (McCandless, 2012). 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).

Though we study micro level low intensity, mostly non-violent conflict, because of the relative lack of knowledge in this area, we refer to the broader literature on violent conflict and food security. Food secure households in an impoverished society are likely to have better access to education and employment which increases the opportunity cost of joining a movement (Taeb, 2004). 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). 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).

While the aforementioned literature on civil conflict provides valuable insights between the links of food security and different types of violence, it is largely silent on social altercations at a lower level that may be caused by basic food insufficiency. We propose that households that are food sufficient will be less prone to low intensity interhousehold and community conflict. Our conjecture is furthered by introducing food sharing as a connection in this linkage. We define food sufficiency as never having difficulty in providing food to all family members in the six months prior to the survey. Low intensity interhousehold and community conflict are defined as experiences of interpersonal or community level conflicts, disputes, disagreements, and social altercations, often non-violent in nature, reported by surveyed households.

We choose to study food sufficiency over food security for the following reasons. Household food security is a multidimensional phenomenon that is difficult to capture without a detailed survey dedicated specifically to that purpose. In addition, food security can affect household conflict through multiple channels, thereby making causal exploration challenging and prone to multiple sources of bias. Instead, we use a binary response to measure one aspect of household food security – whether the household had sufficient food for the entire family over a six-month period. We draw motivation from FAO's Coping Strategy Index (CSI) (Maxwell et al., 2003) which states, "Clearly, food security is about much more than just how much people have to eat…Yet, having "enough" food to eat is clearly the most important outcome of being food secure, and while physiological requirements differ, people largely know whether they have "enough" or not".[2]

Based on the food security and conflict literature, we argue that food sufficient households are less prone to grievances, greed, psychosocial frustration, anger and emotional stress than their food insufficient counterparts. By feeling content, such households would have lower motivation and aggravation of engaging in conflict. In addition, we propose that if food sufficient households show benevolence towards others, they may also be able to avoid interpersonal conflict. These households may express their content through acts of kindness by helping others with food thereby further reducing their chances of getting involved in such interpersonal altercations.

To be circumspect about potential measurement and endogeneity bias, we employ a cautious research design. Our survey instrument was designed to specifically inquire about conflict experiences such as inheritance disputes, disagreement with pastoralists, disputes with other households, conflict over community resources such as the Virunga Park[3], etc.[4]. Given the way we define food sufficiency and the nature of conflicts explored, it is unlikely that such incidences would affect households' likelihood of having sufficient food over a sustained period.

[3] Africa's first national park overseeing the North Kivu region which is a considered a bio-diversity hot spot.
[4] A more detailed description of the incidences considered is depicted in the variable section.

Citing some examples, conflict occurring over Virunga National Park resources[5] has a very limited probability to cause household food insufficiency. While violent conflict occurring from inheritance with immediate family may cause food shocks, we specifically inquire about disputes (alluding to a lower level conflict) over inheritance that is unlikely to cause food insufficiency within a six-month period. Similarly, for every other low-level conflict we explore, food insufficiency during a six-month period is highly improbable. Hence, our cautious approach and the categories of interhousehold and community conflict considered abate reverse causality suspicions to a large extent.

While we are aware that suspicions of endogeneity may be raised with respect to benevolence and conflict, we argue that benevolent attitudes spur from random acts of kindness, an egalitarian belief system, or an innate tendency to help others. Moreover, request for food help by others does not depend on the household, but the help seeker. However, we acknowledge the intricate subjective nature of benevolence and therefore take extreme caution in claiming causality.

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

[5] A common cause for community level conflict due to its natural and wildlife resources and conservation

specific survey questions related to this study. Data for this study was collected from the province of North Kivu, Eastern DRC.

The present administrative unit of the region is divided into six territories or zones. Our survey was conducted in three of these territories – Beni, Lubero and Rutshuru. Since precise population densities are not known and could not be incorporated in the sampling procedure, we used a grid based randomization technique to make the study sample as representative of the population as possible by ensuring each grid in the selected region had equal likelihood of being studied. High-resolution maps from the United Nation's Office for the Coordination of Humanitarian Affairs (UNOCHA) were used to divide each region into 5kmx5km squares. If a square had at least one village, it was assigned a unique number (see Figure 3-5). Thus 626 unique numbers were assigned corresponding to populated squares with 190 in Beni, 272 in Lubero, and 164 in Rushuru territory. The statistical software "R" was used to generate random numbers to select squares for village sampling. The included maps demonstrate the geographic distribution of the selected locations. Squares that could not be surveyed for any reason (e.g. rough geographical terrain or squares that could potentially endanger enumerators) were replaced with the next number. While omitting squares with high levels of conflict from our sample could raise concerns for biased estimates, the actual number of squares that had to be abandoned for such reasons was trivial, and hence not an issue in this study. Village selection used proportional weighting within each square. If a square had three or less villages, all villages were surveyed. If a square had between four and nine villages, three were selected at random; while for squares that had over ten villages, four were chosen at random. The random selection procedure was executed by assigning numbers to each village and using a random number generator to select the village to be studied.

Local extension agents were employed as enumerators for data collection. A household, the unit of analysis for the study, was defined as a group of people sleeping under the same roof and eating together. Enumerators were instructed to interview all households from selected villages. A strict starting location was not enforced since the sample design included the entire village. If the decision maker was absent at the time of visit, the enumerators were asked to move on to the next house and return later. Households for which vital information was missing were dropped from the analysis. Through this process, we obtained a full sample of data from 1763 farming households from 161 communities[6].

Structured questionnaires were used to gather information on household socio-economic and demographic structure, food sufficiency measures, conflict experiences, 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. Respondents did not receive any compensation for participating in the study.

[6] Though our enumerators tried their best to document responses, in many cases households reported villages by their geographic subdivision such as north, south, etc. To overcome this confusion, we refer to all geographic regions as communities.

(b) Variables

The outcome variable of interest is low intensity interhousehold and community conflict[7] experienced by households. To measure conflict, households were asked if they experienced any of the following types of conflict in the past six months: a) conflict with neighbors and fellow villagers; b) disagreement involving Virunga National 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 low intensity interpersonal conflict as the most prevalent in our study areas.

Using household responses of conflict experienced, we constructed four indicative measures of conflict: a) *conflict* is an indicator variable equal to one if the household experienced any kind of conflict and zero otherwise; b) *conflict with individuals* is an indicator variable equal to one if the household has experienced conflict with individual households (i.e. neighboring households or fellow villagers, conflict with landholders or with non-dwelling relatives and pastoralists) and zero otherwise; c) *conflict with groups* is an indicator variable equal to one if the household experienced community level conflict (i.e. 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.

---

[7] We refer to low intensity interhousehold and community conflict as "conflict" for the sake of brevity and fluency.

The main explanatory variable is household level food sufficiency. We asked households, "how often have you had difficulty feeding your entire family in the last six months?" Respondents could choose between three options, namely, "often", "sometimes" or "never". For our analysis, we categorize a household as *food sufficient* if it responded "never"; and *food insufficient* if it responded "often" or "sometimes". Given the discrete nature of response choices, we rule out the possibility of measurement error since it appears unlikely that households would incorrectly claim food sufficiency and that any such error would be systematic. To further guard against any potential systematic error in responses, we inquire about conflict experiences after the food sufficiency question in the survey instrument. To validate the robustness of our measure, we included additional questions in our survey instrument to proxy for households' food sufficiency. An examination of these variables negates the possibility of measurement error. In addition, our summary statistics show that around 56 percent of the households claim to be food insufficient, which is consistent with reported household surveys conducted by WFP (2014) and UNICEF (2010) in DRC and North Kivu. To measure "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*.

While it is impossible to rule out the presence of omitted variables from survey data, we include a large set of control variables from relevant literature to match households. We also include community fixed effects to capture any differences in communities and macro level shocks that could affect households. Control variables included community 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 sufficiency. Education, which may reduce both food insufficiency and conflict, is accounted for through the years of education of the most highly educated member of the household. Assuming diminishing marginal return to education, the variable is included in both 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 insufficiency or conflict, hence we control for various measures of empowerment and voice.

(c) Descriptive statistics

Table 1 presents a cross tabulation of the types of conflict incurred by households and their food sufficiency status. Panel A summarizes the number of households that experience any form of conflict. Overall, about 50% of the sample households reported having experienced some form of conflict. About 43% of the sample households are food sufficient while the remaining 56% are food insufficient. This is consistent with a WFP report on food sufficiency in DRC by province which classifies around 60% households in North Kivu as food sufficient at the time of our survey (WFP, 2014). Panel B shows detailed accounts of the different types of conflict experience reported by households. Approximately 41% were involved in conflicts with other households, while 9% incurred conflict with the community.

The most common type of conflict reported is conflict with neighbors and fellow villagers, followed by disputes over land and disagreements with pastoralists. It should be noted that the number of food sufficient and food insufficient households are not equal in our sample and that some households experienced multiple instances of conflict (between one and twelve different types). As a result, the numbers should be interpreted with caution and is presented to provide a general understanding of the distribution of the two key variables.

Table 1: *Detailed account of conflict reported by households*

	HH claims to be food sufficient	HH claims to be food insufficient	Total number of HH
Panel A: Conflict experience of household			
Number of HH that did not experience any conflict	438	482	920
Number of HH that experienced some kind of conflict	328	515	843
Total number of HH	766	997	1763
Panel B: Type of conflict			
Number of HH that reported conflict with individual HH	429	781	1210
Conflict with neighbors and fellow villagers	129	249	378
Conflict with landholder	100	243	343
Inheritance dispute among non-dwelling family members	73	96	169
Disagreement with pastoralists	127	193	320
Number of HH that reported conflict with groups	96	222	318
Land and resource conflict with rebel forces	61	135	196
Land and resource conflict with government forces	11	37	48
Conflict over community resources including Virunga Park	9	14	23
Others	15	36	51

Source: Authors' calculations based on the survey data.

Note: A single household may incur more than one type of conflict. 'Other' forms of conflict reported include, theft, robbery, sorcery, etc. HH refers to household in the table.

Table 2 presents the mean comparisons for the socioeconomic characteristics of households by food sufficiency status as well as a t-test of means. The last column shows the mean values for the full sample. The first three dependent variables can be interpreted as the proportion of households that experienced conflict. 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)[8]. 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 belongs to a cooperative and three quarters of the respondents have access to some form of technology. Approximately, three fifth of the respondent households have held a position of leadership and influence in the community as measured by their ability to speak in the village council during community dispute resolution.

The summary statistics also show that food sufficient households are different from food insufficient households in terms of socioeconomic and demographic characteristics. For example, the average food sufficient household is significantly larger, comprised of more adult males, has attained a higher level of education and earns more household income than food insufficient households. Furthermore, food sufficient 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 influential positions

[8] 1 USD=925 CDF at the time of the study.

in the community and exhibit benevolence towards others. Food sufficiency status had some variation among communities, 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 sufficient household. Around two thirds of all households help others with food. The descriptive statistics reveal that food sufficient households in our sample are less likely to have written claims over their land compared to food insufficient households, which is counterintuitive. Although this difference is unexpected, our logit estimation shows that the land variable is statistically insignificant in determining selection into treatment.

Table 2. *Summary statistics of main variables*

Variable	Food sufficient households (N=762)	Food insufficient 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)	0.69***	0.55	0.61
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 sufficient and insecure households. *, **, and *** indicate significance at 10%, 5% and 1% levels respectively. Community 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 sufficiency and conflict immediately points to potential endogeneity bias in estimation. Therefore, to estimate causal impacts, we use food sufficiency 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 sufficient, treated and treatment group interchangeably. Similarly, we will interchange between the terms food insufficient, control and control group.

Let T denote our binary treatment variable (T=1 if the household is food sufficient and T=0 otherwise). Let Y_1 denote the outcome (conflict status) of a household that is food sufficient and Y_0 the outcome for the same household had it not been food sufficient; let X be a vector of observable covariates (background characteristics). If T could be randomly assigned to households, estimating the average treatment effects (ATE) would give us the causal impact of being food sufficient on conflict. However, such an experiment that entails providing food sufficiency 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 sufficiency 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 insufficiency 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 sufficiency 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:

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

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

$$ATT = \big[\big(E(Y_1 | \, T = 1) - E(Y_0 | \, T = 0)\big) - (E(Y_0 | \, T = 1) - E(Y_0 | \, T = 0))\big] \qquad (1)$$

Equation 1 shows how the ATT can provide correct estimates by adjusting for selection bias represented by the second term on the right-hand side.

(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 sufficient, 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 between food sufficient and food insufficient households, we can regard the treatment assignment, food sufficiency, 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.

$$0 < Pr\ (\mathrm{T} = 1|\mathrm{X}) < 1 \quad (3)$$

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

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

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 sufficient 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 heterogeneous treatment effects (see Kibriya, Zhang & Xu, 2017; Xie, Brand, & Jann, 2012; Verhofstadt & Maertens, 2014) and is expressed as follows:

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

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 sufficient household to nonfood sufficient households that are closest to its propensity score. For nearest neighbor matching, we use three nearest neighbors with replacement since replacement increases the quality of matching, especially when there are fewer close matches. Kernel matching uses a weighted average of all non-food sufficient households to match it with food sufficient 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 sufficient household with all non-food sufficient households whose propensity scores fall within the predefined neighborhood of the propensity score of the food sufficient 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 sufficiency) 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.

One limitation of propensity score matching is that it can only correct for selection on observables but not for potential unobservable confounders. While unobservable variables cannot be controlled for, we use the Rosenbaum test for hidden bias to check how much our estimates may have been affected by unobservable confounders.

5. RESULTS AND DISCUSSION

(a) Determinants of household food sufficiency

Table 3 presents the results from the logit model to determine the likelihood of being food sufficient, given observable characteristics of the household. The logit model has a pseudo R^2 of 0.18 and correctly predicts the food sufficiency status of the sample households 71% of the time. Overall, the following variables are significant in explaining the likelihood that a household is food sufficient: 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 sufficient.

The results show that the household education positively affects the probability of the household being food sufficient. 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 sufficiency 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 sufficiency 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 sufficiency.

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

Variable	Coefficient	Standard error	Marginal effect
Dependent variable: =1 if household is food sufficient =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)	
Community 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. Community and religion controls have been omitted from the table to save space.

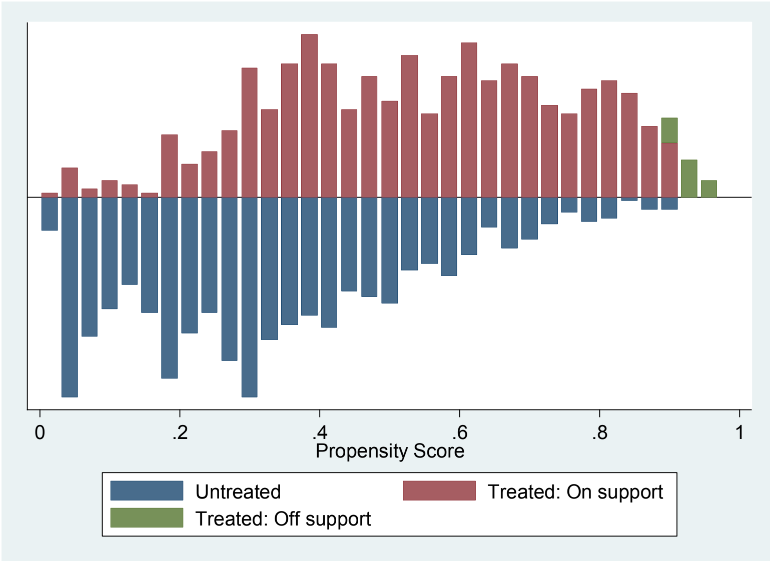
Access to technologies such as mobile phones, radios, television, bicycle and motorized vehicles increases the likelihood of being food sufficient. Increased access to information and communication technologies may reduce information asymmetry as well as transaction cost for farmers, thereby making them more food sufficient. Having access to basic services such as safe drinking water and cooking fuel also increases the probability of being food sufficient. Given that a large fraction of rural households use fuelwood for cooking, it would explain why access to cooking fuel may affect food sufficiency. Furthermore, access to agricultural extension services increases the likelihood of being food sufficient. 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. Households with members who hold influential positions within the community make a household more likely to be food sufficient. Holding important positions in the community can help households gain access to credit and other agricultural services via increased social capital. Finally, certain community specific effects appear to positively influence the probability of being food sufficient. To save space, the details of the communities have been excluded from the table. It may well be that these are regions associated with higher overall production.

(b) *Impact of food sufficiency on conflict*

(i) *Propensity score matching results*

Figure 1 shows the distribution of propensity scores between food sufficient and food insufficient 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 sufficient and food insufficient households to justify using a matching technique for estimation. Figure 6 in the Appendix also shows the box plots for the propensity score distributions.

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 sufficient 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 insufficient 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.



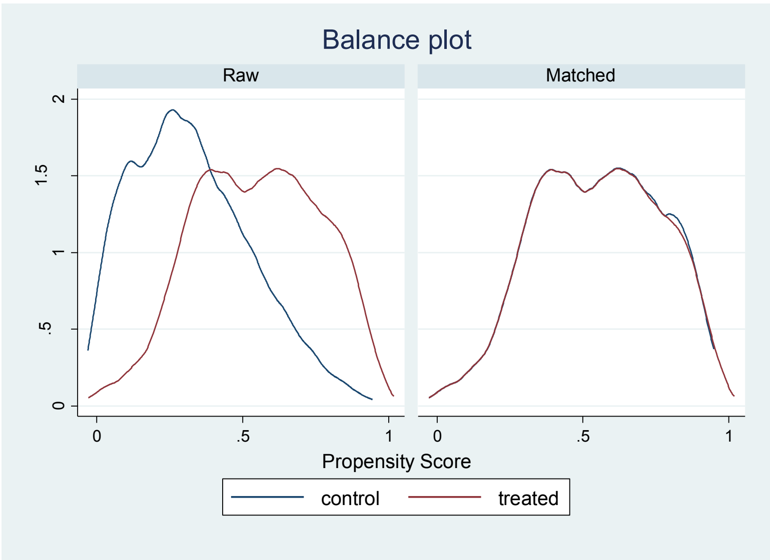


Figure 1. *Distribution of propensity scores and the region of common support. Note: Treated on support indicates households in the food sufficient group that find a suitable match while treated off support indicates households that do not find a match in the food insufficient group. Untreated refers to households that are not food sufficient.*

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, i.e. food sufficiency. The dependent variable we chose is an indicator variable with value one if the spouse of the household head inherits land upon their death, and 0 otherwise. The result shown in Table *10*10 in the Appendix reveals that the coefficient associated with food sufficiency 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 most likely no omitted variables correlated with being food sufficient 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*

Covariate	Sample	Mean: Treated	Mean: 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 community 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 sufficiency on household conflict for the different matching algorithms. Consistent across all methods, we find that food sufficiency reduces the probability that a household experiences conflict. Overall, households that are food sufficient 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 sufficient. The coefficients and significance values are similar across the different matching methods. On average, food sufficient households are approximately 10 percentage points less likely to experience conflict than their food insufficient counterparts.

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

Outcome Variable	Treatment variable: food sufficiency		
	Nearest-neighbor (3)	Kernel matching	Radius matching
Probability of conflict	-0.095***	-0.101***	-0.076 ***
	(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*	-0.026*
	(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 shown 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 sufficiency reduces the probability that a household will engage in conflict with other households by about 9 to 10 percentage points. The probability of food sufficient households engaging in community conflict reduces by 3 to 4 percentage points compared to the likelihood of conflict had the household not been food sufficient. Finally, food sufficient households experience 0.30 to 0.33 fewer types of conflict on average than food insufficient 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 sufficient households experience lower levels of conflict with other households and with groups within the community. Food sufficiency reduces cause for grievance and general frustrations which can translate to aggressive and anti-social behavior in society.

Table 6 compares the performance of the three matching algorithms used. For all three matching techniques used, overall the standardized mean bias for covariates 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 columns show 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 heterogeneous effect of food sufficiency conditional on benevolence

In the last section, we found that food sufficiency reduces conflict at the household and community level. In this section, we investigate the heterogeneous effects of being food sufficient. In particular, we test whether helping others with food affects the probability of conflict for food sufficient and food insufficient households differently. Before delving into regressions, we display the summary statistics for our main conflict variables by household food sufficiency as well as benevolence status in Table 7.

Table 7: Summary of Conflict by household food sufficiency and benevolence

	Household has sufficient food (1)		Household does not have sufficient food (2)		Difference in means between food sufficient and food insufficient households (3)	
Conflict measure	Benevolent (a)	Non-benevolent (b)	Benevolent (a)	Non-benevolent (b)	Benevolent (a)	Non-benevolent (b)
Probability of conflict	0.39***	0.58	0.50	0.54	***	-
Probability of conflict with individual households	0.37***	0.52	0.45	0.49	***	-
Probability of conflict with groups	0.9***	0.18	0.17	0.17	***	-
Number of types of conflict	0.62***	1.00	0.95	1.10	***	-

Source: Authors' calculations based on survey data.

Notes: We use t-tests to test for equal means for both benevolent and non-benevolent households, for a given food sufficiency level; and between food sufficient and food insufficient households, for a given benevolence level. *, **, and *** indicate significance at 10%, 5% and 1% levels respectively. The asterisks in column (1a) show that food sufficient households that are benevolent experience significantly lower levels of conflict than food sufficient households that are not benevolent. The absence of asterisks in column (2a) shows that the mean levels of conflict for benevolent and non-benevolent households that are food insufficient are similar. Similarly, the asterisks in column (3a) show that food sufficient households that are benevolent experience significantly lower levels of conflict that food insufficient households; while column (3b) shows that if the household is not benevolent, there are no significant differences in the mean level of conflict experienced between food sufficient and food insufficient households.

A preliminary comparison shows that for all four measures, conflict is significantly lower for food sufficient households that are benevolent compared to food sufficient households that are not benevolent. In contrast, if the household does not have sufficient food, there is no significant difference between benevolent and non-benevolent households. The last two columns show that among benevolent households, food sufficient ones have a lower probability of conflict than food insufficient ones. However, in the absence of benevolence, the difference does not appear to be significant. Since these differences in means could occur if food sufficient and insufficient households were systematically different, we proceed with a propensity score matching analysis.

To conduct this estimation, we subsample the data into households that show benevolence towards others, and households that do not. For each subsample, we estimate a separate ATT and compare the results. This allows us to compare the conflict outcome for food sufficient households with the same households had they not been food sufficient, conditional on benevolence. Table 8 shows the results of the estimation. It is immediately obvious from panel A that conditional on benevolence, food sufficiency statistically significantly reduces conflict for the average household. This result holds across all matching techniques. Depending on the algorithm used, the absolute difference in the average probability of conflict experienced by a food sufficient household that shows benevolence and a food insufficient household that shows benevolence lies between 8.1 and 13.8 percentage points for all kinds of low intensity local conflict; between 8.3 and 12.4 percentage points in case of conflict with individual households; and between 2.6 and 5.3 percentage points in case of conflict with groups or the community. Food sufficient households that show benevolence also experience 0.24 to 0.38 fewer types of conflicts than food insufficient households that show benevolence. However, the results in panel B show that if the household does not show benevolence, the effect of food sufficiency on conflict disappears. That is, conditional on non-benevolence, the expected probability of conflict is the same for food sufficient and food insufficient households.

Table 8: Effect of food sufficiency conditional upon benevolence of household

Outcome Variable	Matching Algorithm		
	NNM (3)	KM	RM
Panel A: Effect of food sufficiency given household is benevolent			
Probability of conflict	-0.106**	-0.138***	-0.081*
	(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 sufficiency 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.

To summarize, the above table shows the following results. First, if the household is benevolent, being food sufficient reduces its probability of low intensity interhousehold and community conflict. Second, if the household is not benevolent, food sufficient and food insufficient households have the same probability of conflict. Therefore, we can conclude that a food sufficient household experiences lower conflict only if the household is also benevolent.

The covariate balance test for the matching process is shown in the Appendix in Table 11 (for benevolent households) and Table 12 (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 13 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 and selection on unobservables

Table 9 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 sufficient are very similar to the results from the matching algorithms in Table 5. On average, food sufficiency reduces the likelihood that a household experiences conflict by about 10 percentage points for overall conflict; 9.5 percentage points for conflict with other households and 3.6 percentage points for conflict with groups within the community. On average, food sufficient households are likely to experience 0.31 fewer types of conflict compared to their food insufficient 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 sufficiency given benevolence is shown in the fourth column. The estimates are same as the propensity score estimates shown in

Table 8. This result further substantiates our previous finding that conditional on benevolence, food sufficiency reduces conflict for households.

Table 9: Doubly robust estimation and Rosenbaum critical level of hidden bias results

Outcome Variable	Treatment: food sufficiency		Treatment: food sufficiency 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. 124***	
	(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 errors are 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 sufficient 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 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 Γ =1, the results are similar to our estimates. With food sufficiency 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 sufficient by a factor of 1.65 (65%) to 5.5 (450%) to overturn the significance of our ATT estimates. When the treatment is food sufficiency 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%) for the estimated ATTs to lose their statistical significance. Based on these results we can conclude that our findings are robust to potential hidden bias from unobserved covariates.

6. CONCLUDING REMARKS

By exploiting survey data of 1763 households collected from three territories in the North Kivu province of eastern DRC, we study the impact of food sufficiency and foods sharing on low intensity interhousehold and community conflict. Since food sufficient households may be systematically different from food insufficient households, we use the quasi-experimental method of propensity score matching to control for any preexisting differences. This allows us to compare conflict experiences of a food sufficient household with essentially the same household had it not been food sufficient, thus allowing us to plausibly isolate the effect of food sufficiency on household conflict. By exploiting heterogeneous treatment effects, we find empirical evidence to support that food sufficiency can reduce the probability of conflict for households only in the presence of benevolence. Food sufficient households that show benevolence towards others reduce their overall probability of conflict by an average of 13.8 percentage points; a reduction of up to 12.4 percentage points in the probability of conflict against individual households and a reduction of up to 5.3 percentage points in the probability of conflict against groups within the community. In addition, food sufficient households that are also benevolent experience fewer types of conflict on average.

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 for any potential bias arising from unobservable confounders. Although we take extreme caution to claim causality, our checks and balance tests do not indicate concern for violations of the assumptions used, suggesting that a causal claim of our finding is plausible, at the least.

While the existing literature mostly uses cross country or district level data for analyses of civil wars and conflicts, we shed light on the facets of interhousehold and community conflicts that most frequently do not make headlines and are subsequently ignored. Our findings advance the understanding of the intricate relationship between food sufficiency and conflict 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 (Barrett, 2001; Nunn & Qian, 2014). Our approach of analyzing the connection between household level food sufficiency and low intensity local conflict can offer new insights to program implementers and evaluators.

Hence, our most significant contribution may be emphasizing the value of collecting and studying micro level low intensity conflict experiences in fragile societies. Our findings show that food sufficiency alone cannot reduce low intensity interhousehold and community level conflict unless accompanied by benevolent approaches. As such, our results illuminate the need to study benevolent behavior in society. This may be a way forward for researchers to further investigate the effect of such approaches in other settings and to examine its role on the different levels and facets of conflict. In addition, it may be useful to development practitioners to encourage benevolent practices in society that can complement poverty alleviation and conflict reduction initiatives.

7. REFERENCES

Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, *74*(1), 235-267.

Arezki, M. R., & Bruckner, M. (2011). *Food prices and political instability* (No. 11-62). International Monetary Fund.

Barnett, J., & Adger, W. N. (2007). Climate change, human security and violent conflict. *Political geography*, *26*(6), 639-655.

Barrett, C. B. (2001). Does food aid stabilize food availability? *Economic development and cultural change*, *49*(2), 335-349.

Bellemare, M. F. (2015). Rising food prices, food price volatility, and social unrest. *American Journal of Agricultural Economics*, *97*(1), 1-21.

Berazneva, J., & Lee, D. R. (2013). Explaining the African food riots of 2007–2008: An empirical analysis. *Food Policy*, *39*, 28-39.

Bessler, D. A., Kibriya, S., Chen, J., & Price, E. (2016). On Forecasting Conflict in the Sudan: 2009–2012. *Journal of Forecasting*, *35*(2), 179-188.

Bora, S., Ceccacci, I., Delgado, C., & Townsend, R. (2010). World Development Report 2011: Food sufficiency and Conflict. *Washington, DC: Agriculture and Rural Development Department, World Bank*.

Brinkman, H. J., & Hendrix, C. S. (2011). *Food insufficiency and violent conflict: Causes, consequences, and addressing the challenges*. World Food Programme.

Brück, T., D'Errico, M., & Pietrelli, R. (2017). The Effects of Violent Conflict on Household Resilience and Food sufficiency: Evidence from the 2014 Gaza Conflict.

Burke, M. B., Miguel, E., Satyanath, S., Dykema, J. A., & Lobell, D. B. (2009). Warming increases the risk of civil war in Africa. *Proceedings of the national Academy of sciences*, *106*(49), 20670-20674.

Bushman, B. J., DeWall, C. N., Pond, R. S., & Hanus, M. D. (2014). Low glucose relates to greater aggression in married couples. *Proceedings of the National Academy of Sciences*, *111*(17), 6254-6257.

Bush, R., & Martiniello, G. (2017). Food Riots and Protest: Agrarian Modernizations and Structural Crises. *World Development*, *91*, 193-207.

Caliendo, M., and S. Kopeinig. 2008. Some Practical Guidance for the Implementation of Propensity Score Matching. Journal of Economics Surveys 22 (1): 31–72.

Cohen, M. J. (1993). Hunger 1994: transforming the politics of hunger. *Bread for the World Institute, Silver Spring, MD*.

Carter, K. N., Kruse, K., Blakely, T., & Collings, S. (2011). The association of food security with psychological distress in New Zealand and any gender differences. *Social science & medicine*, *72*(9), 1463-1471.

Cohen, M. J., & Pinstrup-Andersen, P. (1999). Food sufficiency and conflict. *Social Research*, 375-416. Food sufficiency, Justice and Peace (2002). FAO.

Collier, P., & Hoeffler, A. (2004). Greed and grievance in civil war. *Oxford economic papers*, *56*(4), 563-595.

Chilton, M., & Booth, S. (2007). Hunger of the body and hunger of the mind: African American women's perceptions of food insecurity, health and violence. *Journal of nutrition education and behavior*, *39*(3), 116-125.

Cook, T. D., Shadish, W. R., & Wong, V. C. (2008). Three conditions under which experiments and observational studies produce comparable causal estimates: New findings from within-study comparisons. *Journal of policy analysis and management*, *27*(4), 724-750.

Crump, R. K., Hotz, V. J., Imbens, G. W., & Mitnik, O. A. (2008). Nonparametric tests for treatment effect heterogeneity. *The Review of Economics and Statistics*, *90*(3), 389-405.

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and statistics*, *84*(1), 151-161.

Fearon, J. D., Humphreys, M., & Weinstein, J. M. (2009). Can development aid contribute to social cohesion after civil war? Evidence from a field experiment in post-conflict Liberia. *The American Economic Review*, *99*(2), 287-291.

Global Humanitarian Report-An Overview 2015. UN Office for the Coordination of Humanitarian Affairs

Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies*, *65*(2), 261-294.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The review of economic studies*, *64*(4), 605-654.

Heflin, C. M., Siefert, K., & Williams, D. R. (2005). Food insufficiency and women's mental health: findings from a 3-year panel of welfare recipients. *Social science & medicine*, *61*(9), 1971-1982.

Hendrix, C. S., & Salehyan, I. (2010). After the Rain: Rainfall Variability, Hydro-Meteorological Disasters, and Social Conflict in Africa.

Hendrix, C., & Brinkman, H. J. (2013). Food insufficiency and conflict dynamics: Causal linkages and complex feedbacks. *Stability: International Journal of Security and Development*, *2*(2).

Homer-Dixon, T. F. (1994). Environmental scarcities and violent conflict: evidence from cases. *International security*, *19*(1), 5-40.

Homer-Dixon, T. F. (1999). Environment, scarcity, and conflict. *Princeton University*.

Humphreys, M., & Weinstein, J. M. (2008). Who fights? The determinants of participation in civil war. *American Journal of Political Science*, *52*(2), 436-455.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and statistics*, *86*(1), 4-29.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of economic literature*, *47*(1), 5-86.

Kahl, C. H. (2006). *States, scarcity, and civil strife in the developing world*. Princeton University Press.

Kibriya, S., Xu, Z. P., & Zhang, Y. (2017). The negative consequences of school bullying on academic performance and mitigation through female teacher participation: evidence from Ghana. *Applied Economics*, *49*(25), 2480-2490.

Leuveld, K. et al. (Forthcoming). The impact of agricultural extension and input subsidies on knowledge, input use and food sufficiency in Eastern DRC

Macrae, J., & Zwi, A. B. (1992). Food as an instrument of war in contemporary African famines: a review of the evidence. *Disasters*, *16*(4), 299-321.

Martin-Shields, C. & Stojetz, W. (2017). Framing the Relationship Between Food sufficiency and Violent Conflict Data: A Clustering and Typology Approach.

McCandless, E (2012). *Peace Dividends and Beyond: Contributions of Administrative and Social Services to Peacebuilding*. New York: UN/PBSO.

Maxwell, D., Watkins, B., Wheeler, R., & Collins, G. (2003). The coping strategies index: A tool for rapidly measuring food security and the impact of food aid programs in emergencies. *Nairobi: CARE Eastern and Central Africa Regional Management Unit and the World Food Programme Vulnerability Assessment and Mapping Unit*.

Mercier, M., Lionel Ngenzebuke, R. L. Verwimp, P. (2017) Violence exposure and deprivation: Evidence from the Burundi civil war.

Messer, E., Cohen, M. J., & d'Costa, J. (1998). *Food from peace: Breaking the links between conflict and hunger* (Vol. 24). Intl Food Policy Res Institute.

Miguel, E., Satyanath, S., & Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of political Economy*, *112*(4), 725-753.

Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *The American Economic Review*, *104*(6), 1630-1666.

Østby, G. (2008). Polarization, horizontal inequalities and violent civil conflict. *Journal of Peace Research*, *45*(2), 143-162.

Pinstrup-Andersen, P., & Shimokawa, S. (2008). Do poverty and poor health and nutrition increase the risk of armed conflict onset? *Food Policy*, *33*(6), 513-520.

Poverty and household living conditions in the North-Kivu Province. 2009. UNDP Report.

Raeymaekers, T. (2008). Conflict and food sufficiency in Beni-Lubero: back to the future? *Alinovi, Hemrich y Russo (2008), págs*, 169-195.

Raleigh, C (2010). 'Political Marginalization, Climate Change, and Conflict in Sahelian States'. *International Studies Review* 12(1): 69–86.

Richards, P. (1998). *Fighting for the rain forest: war, youth & resources in Sierra Leone* (No. Reprinted Ed.). James Currey Ltd.

Rojas, M., & Guardiola, J. (2017). Hunger and the experience of being well: Absolute and relative concerns. *World Development*, *96*, 78-86.

Rosenbaum, P. R. (2002). Covariance adjustment in randomized experiments and observational studies. *Statistical Science*, *17*(3), 286-327.

Rosenbaum, P. R. (2002). Observational studies. In *Observational Studies* (pp. 1-17). Springer New York.

Rosenbaum, P., & Rubin, D. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika, 70*(1), 41-55.

Rubin, D. B. (2001). Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*(3), 169-188.

Salehyan, I. (2008). From climate change to conflict? No consensus yet. *Journal of Peace Research*, *45*(3), 315-326.

Schomerus, M., & Allen, T. (2010). Southern Sudan at odds with itself: Dynamics of conflict and predicaments of peace.

Sneyers, A. (2017). Food, Drought and Conflict: Evidence from a Case-Study on Somalia.

Stearns, J. (2012). North Kivu: The background to conflict in North Kivu province of eastern Congo. Usalama Project, Rift Valley Institute, London, 2012.

Stewart, F. (1998). Food aid during conflict: can one reconcile its humanitarian, economic, and political economy effects. *American Journal of Agricultural Economics*, *80*(3), 560-565.

Stewart, F. (2011). Inequality in Political Power: A fundamental (and overlooked) dimension of inequality. *The European Journal of Development Research*, *23*(4), 541.

Taeb, M. (2004). Agriculture for Peace: Promoting agricultural development in support of peace.

The International Fund for Agricultural Development (IFAD), United Nations. IFAD in the Democratic Republic of the Congo.

UNICEF, M. (2000). Multiple indicator cluster survey (MICS).

United Nations (2015). North Kivu Factsheet: MONUSCO. United Nations Organisation Stabilization Mission in the Democratic Republic of Congo.

Verhofstadt, E., & Maertens, M. (2014). Can agricultural cooperatives reduce poverty? Heterogeneous impact of cooperative membership on farmers' welfare in Rwanda. *Applied Economic Perspectives and Policy*, ppu021.

Vlassenroot, K., & Huggins, C. (2005). Land, migration and conflict in eastern DRC. *From the ground up: land rights, conflict and peace in sub-Saharan Africa*, 115-195.

Vlassenroot, K., & Raeymaekers, T. (2008). Crisis and food sufficiency profile: The Democratic Republic of the Congo. *Beyond relief: food sufficiency in protracted crises*, 157-168.

Weezel, S.V. (2017). Estimating the effect of conflict on food supply at the national level.

White, S. C., Fernandez, A., & Jha, S. (2016). Beyond the grumpy rich man and the happy peasant: mixed methods and the impact of food security on subjective dimensions of wellbeing in India. *Oxford Development Studies*, *44*(3), 332-348.

Winne, M. (2010). *Food Rebels, Guerrilla Gardeners, and Smart-Cookin' Mamas: Fighting Back in an Age of Industrial Agriculture*. Beacon Press.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

World Bank (2016). “Poverty and Shared Prosperity 2016: Taking on Inequality.”

World Bank (2011). *World Development Report 2011: Conflict, Security, and Development*. Washington, DC: World Bank.

World Food Programme (WFP). 2014. Democratic Republic of Congo: Comprehensive Food Security and Vulnerability Analysis (CFSVA). Rome: WFP.

World Food Programme (WFP). 2016. Democratic Republic of Congo: Comprehensive Food sufficiency and Vulnerability Analysis (CFSVA). Rome: WFP.

Xie, Y., Brand, J. E., & Jann, B. (2012). Estimating heterogeneous treatment effects with observational data. *Sociological methodology*, *42*(1), 314-347.

8. APPENDIX

Table 10. Estimation results from the placebo regression.

Dependent variable: spouse of interviewee inherits land	Coefficient	Standard error
Food sufficient	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 11. *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 community 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 12. 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 community 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 13: 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 2: Map of DRC showing North Kivu

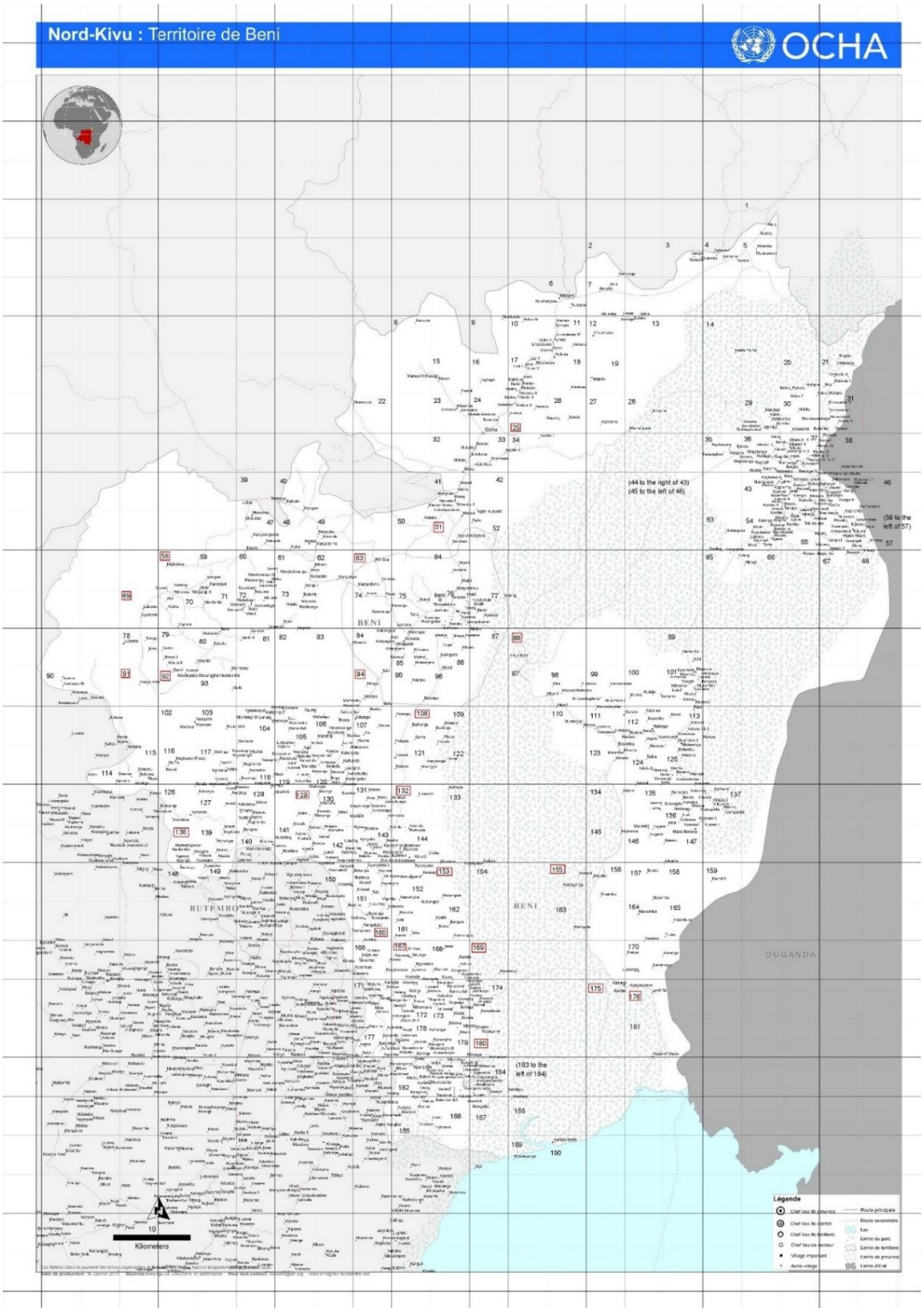


Figure 3: Grid map of Beni territory

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

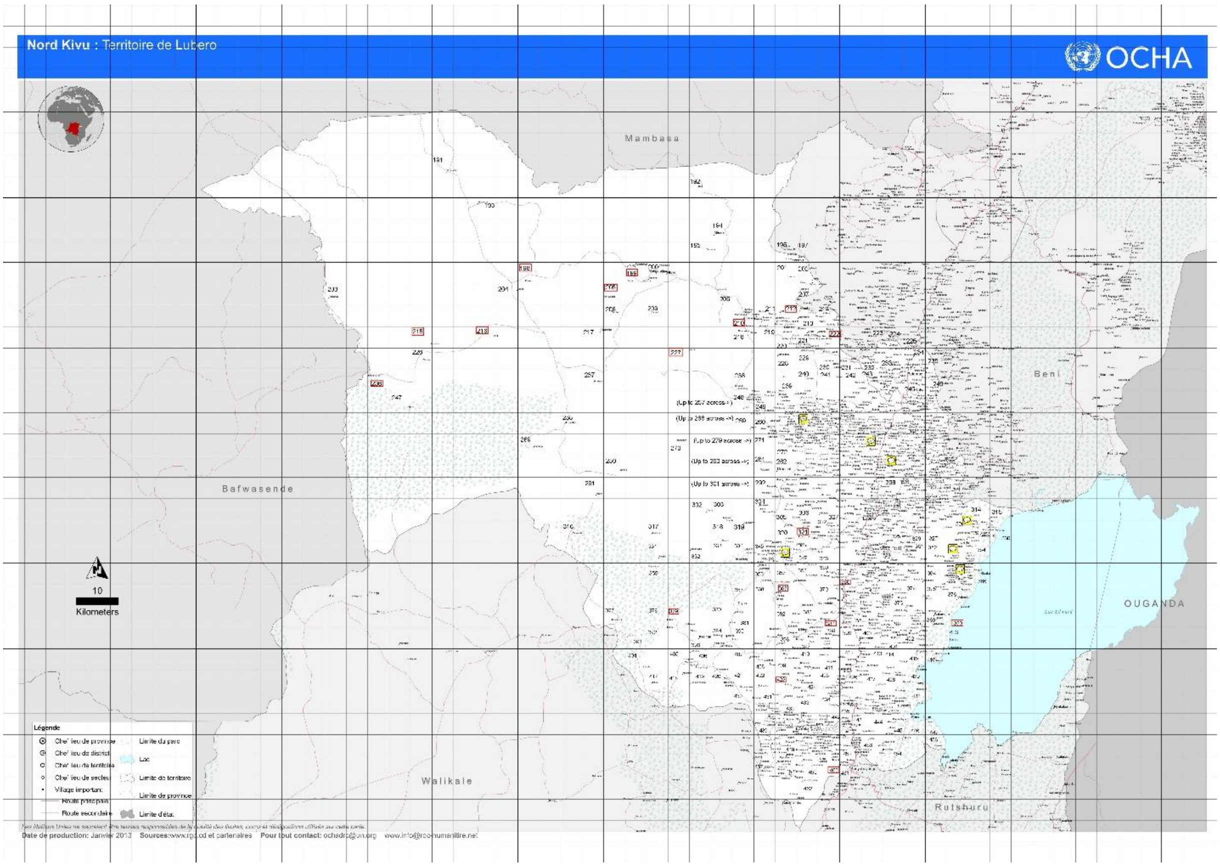


Figure 4:Grid map of Lubero territory

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

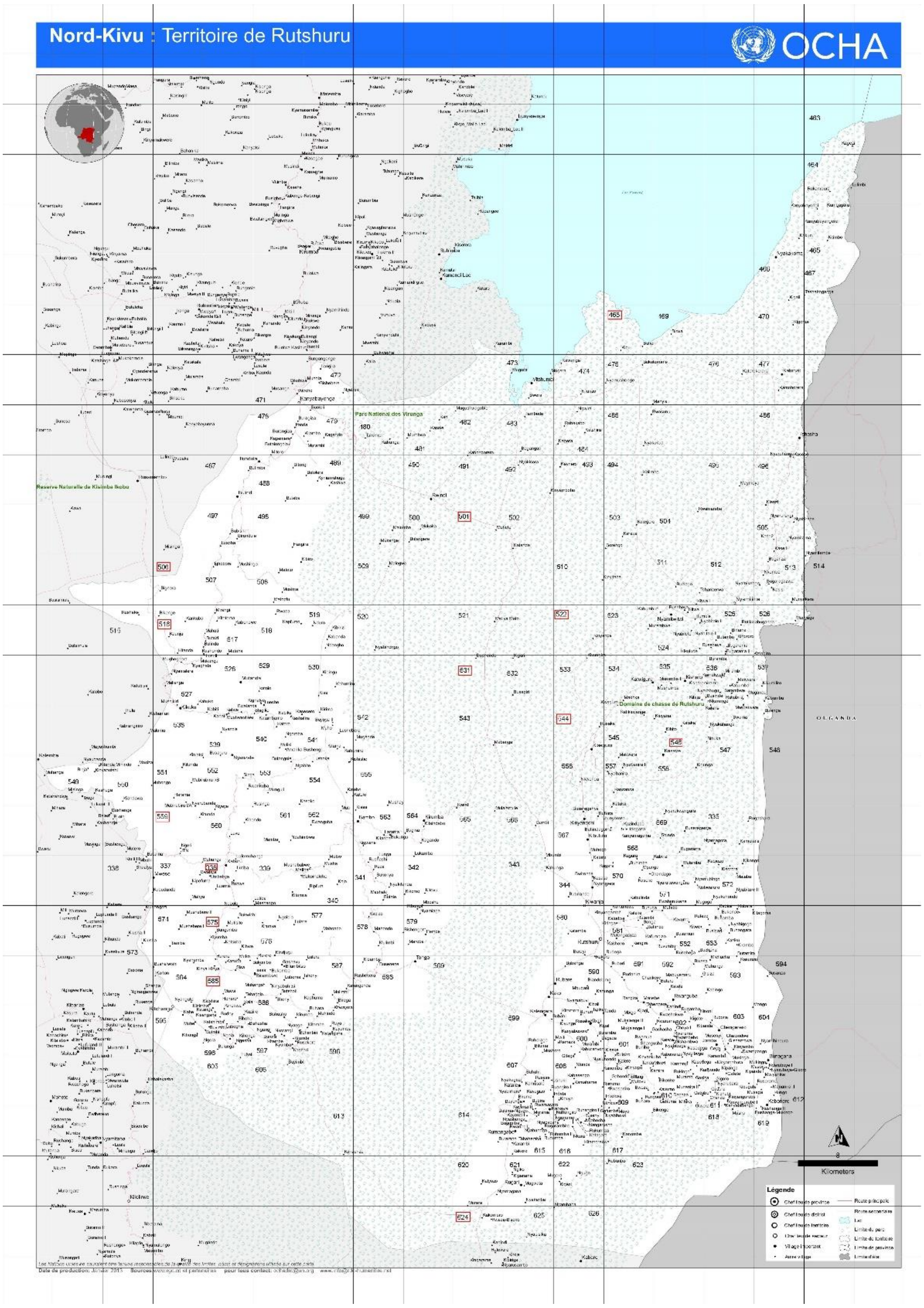


Figure 5: Grid map of Rutshuru territory

Source: The United Nations Office for the Coordination of Humanitarian Affairs *(OCHA),*

available at www.rgc.cd

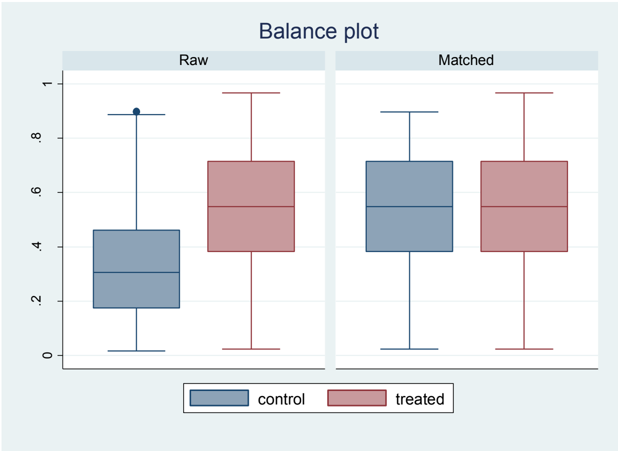


Figure 6: Box plot to show distribution of propensity score between treated and control groups before and after matching

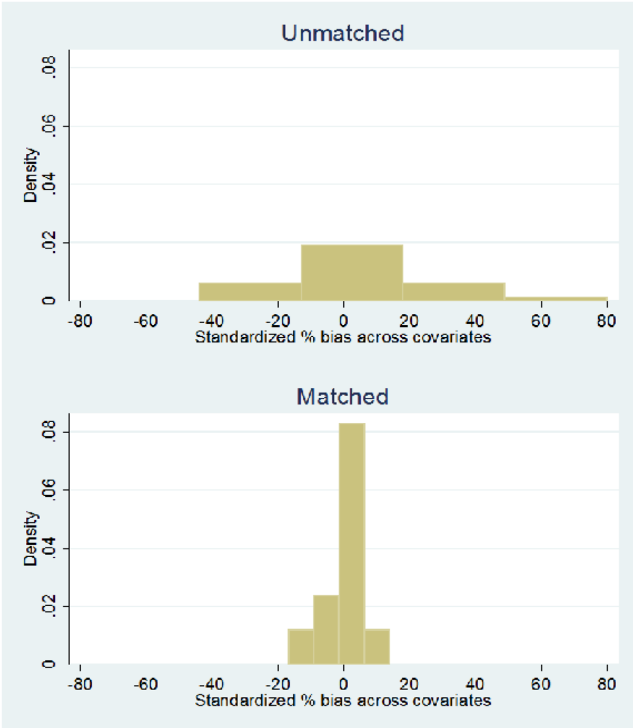


Figure 7:Histogram of standardized differences before and after matching

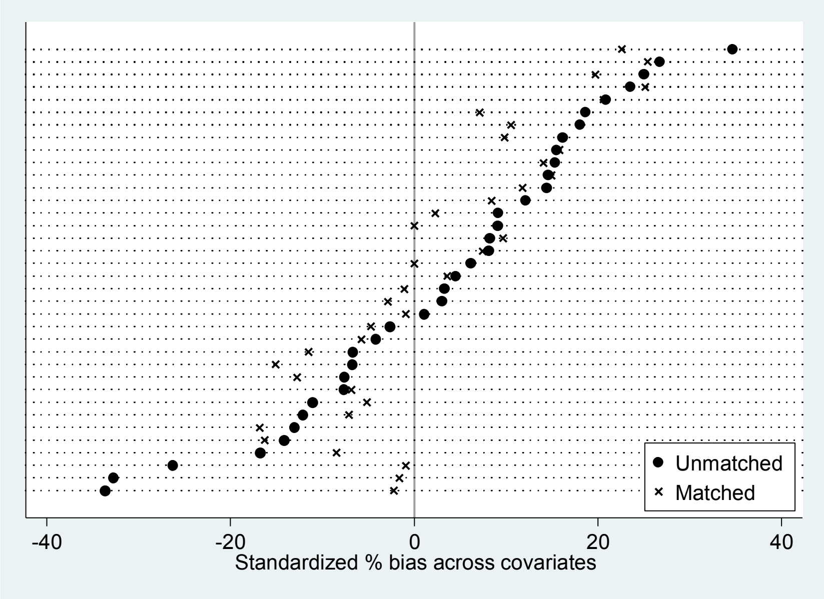


Figure 8: Graph of standardized differences before and after matching

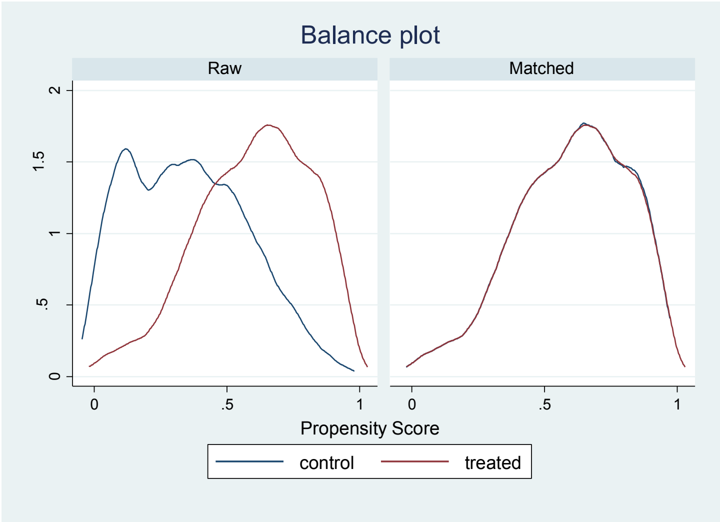


Figure 9: Distribution of propensity scores in unmatched and matched samples for benevolent households

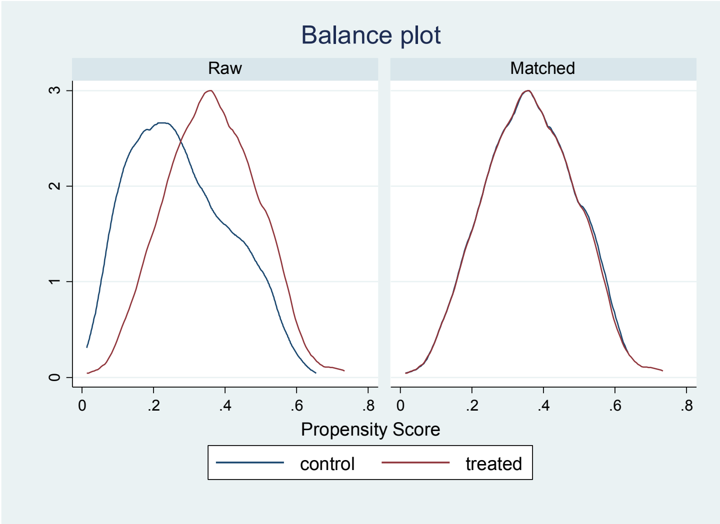


Figure 10:Distribution of propensity scores in unmatched and matched samples for non-benevolent households