THE IMPACT OF HOUSEHOLD ENERGY TRANSITION ON HOUSEHOLD WELFARE INDICATORS IN TANZANIA

Kevin Rugaimukamu

1st October 2018

Abstract

Household energy transitions have been linked to improved household welfare indicators, such as health and schooling. This paper looked at the impact of household energy transitions on household welfare indicators in Tanzania. Specifically, the paper looked at the impact of household's use of modern cooking fuels and the use of electricity for lighting on household welfare indicators. The study used survey data from Tanzania and employed Propensity score techniques to ascertain the impacts of household's energy transitions in Tanzania. The study found evidence of a reduction in incidences of respiratory diseases among children and use of charcoal for households using modern cooking fuels while the use of electricity for lighting was associated with improved evening study hours, education attainment and passing of examinations. Moreover household electrification was found to affect household time use and fertility. The results provide result based reasons for policies to be geared towards improving access to modern energy fuels in terms of cooking and lighting, and ease any constraints towards full energy transitions by households so to achieve other development goals of the country.

1 Introduction

Tanzania's population use wood fuels (charcoal and firewood) and electricity as their main cooking and lighting fuels respectively. Over 90 percent of the Tanzanian households use wood fuels for cooking (National bureau of statistics, 2015a), with the use of charcoal prominent in the urban areas and the use firewood more prominent in the rural areas. Nevertheless, the use of alternative fuels for cooking has increased the urban areas, with the largest increases observed in Dar-es-salaam, where the proportions of households using alternative fuels for cooking increased from 7.2 percent in 2008 to 12.5 percent in 2014 (National bureau of statistics, 2015a),. On the other hand, the population using electricity for lighting has increased from 13 percent in 2008/09 to 23.5 percent in 2014/15. Though the electrification rate in the villages is still very low at 7.1 percent.

The Tanzanian household energy use scenario depicts a continued increase in household electrification annually and a slow but gradual shift to household use of alternative fuels, with the most of this shift taking place in the urban areas. The government has been doing its part to smoothen household energy transition in Tanzania by putting in place facilitating polices. It's evident that more must be done for the transition to manifest. The best way to warrant such transitions to be fast tracked is providing evidence-based importance of such transitions to household welfare. Bonan et al, (2016) points out the importance of establishing impacts of household energy transitions and link them to economic development, as portrayed in goal number 7 of the sustainable development goal agenda.

The use of improved cook stoves/ modern cooking fuels is associated with a reduction of household's use of wood fuels and consequently reducing the pressure on forests (Brook et al., 2016; Bensch and Peters, 2015). Moreover, the reduced use of wood fuels is associated with a reduction of indoor air pollution linked to household member's incidences of respiratory infections, especially for women and children. Analogously, household electrification is associated with positive schooling outcomes, such as increase in years of schooling (Khandker et al., 2012), reduction of indoor air pollution and thus a reduction in household's members incidences of respiratory infections due to use of kerosene and other traditional sources of lighting. Furthermore, household electrification has been linked to improved household's use of information technologies which increases household's access to information on issues such as family planning.

This study, using the 2014/15 Tanzania National Panel Survey and the 2015/16 Tanzania Demographic and Health Survey and Malaria Indicator Survey employs propensity score matching techniques to substantiate the impact of household energy transition, both in terms of cooking and lighting on the household welfare in Tanzania. Thus, the paper answers two key research question; what is the impact of the household's use of modern cooking fuels (LPG and Electricity) on household's welfare indicators in Tanzania? and what is the impact of the household's use of electricity on household welfare indicators in Tanzania? To the best of our knowledge this is the first paper in Tanzania that comprehensively and in totality looks at the impact of household energy transition on household welfare indicators in Tanzania.

Specifically, in terms of cooking this study adds to the few existing studies that have a proper quantitative impact analysis of household's use of modern cooking fuels in Tanzania (Alem et al., 2015), furthermore, to the best of our knowledge this study provides one of the first few evidences of the impacts of household's use of modern cooking fuels on children's respiratory health in Tanzania. On the other hand, with regards to impact of household electrification this study adds to few existing impact studies of electrification in Sub-Saharan Africa and takes a comprehensive approach by investigating the impact of household electrification on a range of outcomes, including energy expenditures, schooling outcomes, children's health and fertility. Although Aevarsdottir et al, (2017), made a similar attempt in Tanzania, their study focused on the impacts of electrification from solar lamps in the rural areas. Our study looks at the use of electricity (both grid and off-grid) and studies its impacts not only for the rural area, but rather for the whole country (full sample) and sub samples in the urban and rural areas, thus gets the differential impacts in different contexts within the country. Furthermore, to the best of our knowledge, this study provides he first evidence of household electrification impacts on fertility in Tanzania.

2 Literature review

This section reviews literature with regards to impact of household use of modern cooking fuels/improved cook stoves and impacts of electrification on household welfare indicators. The first part of the review looks at the impacts of modern cooking fuels/improved cook stoves while the second part reviews studies on impacts of electrification.

2.1 Impact of improved cookstoves and modern energy cooking fuels

Several studies on impact of improved cook stoves and clean energy have been done over the years covering diverse groups around the world. Most prominently, studies from Asia have dominated the scene, these include Brooks (2014), Lewis (2015), Jain (2014), Brook et al, (2016), Lewis et al, (2017) and Hannah et al, (2016) in India. Smith et al, (2011) in Guatemala, Andandari et al (2014), Putra et al., (2017), and Hnyine et al (2015) in Indonesia. Others include Yu (2011) in China and Vahlne and Ahlgren (2014) in Vietnam. Nevertheless studies from Africa, particularly Sub Saharan Africa are still few and highly dispersed, these include studies such as Bruwen and Levine (2012) in Ghana, Beltramo and Levine (2013) in rural Senegal, Bensch and Peters (2015) in Burkina Faso, Yip et al, (2017) in Kenya, Masatsugu and Pattanayak (2017), Alem et al (2015), Bwenge (2011) and Holmes (2010) in Tanzania.

These studies differ in terms methodologies used, based on the type of data used and the study design. Most papers either used randomized control trials (Bruwen and Liven, 2012; Smith et al, 2011; Hannah et al, 2016; Bensch and Peters, 2015; Beltramo and Levine, 2013; Dresen et al, 2014; Alem et al, 2015) or quasi experimental methods (Lewis et al, 2017; Brook et al, 2016; Adrianzen 2013; Yu 2011; Vahlne and Ahlgren 2014; Yip et al 2017; Tronsco et al, 2013; Jain, 2014; Lewis, 2015; Andadari et al, 2014; Brooks, 2014; Masatsugu and Pattanayak (2017)). Nevertheless a few studies have also done a qualitative exploratory impact analysis of improved and modern cooking stove use on the household's welfare (Bwenge, 2011; Holmes, 2010).

An array of outcomes have been studied with regards to the impacts of improved and clean cook stoves on household welfare, these include but not limited to fuel use, cooking time and time use for biomass collection (Bruwen and Levine, 2012; Lewis et al, 2017; Brook et al, 2016; Adrianzen, 2013; Lewis, 2015; Bensch and Peters, 2015; Beltramo and Levine, 2015; Hnyine et al, 2015; Putra et al, 2017; Jain, 2014; Dresen et al, 2014; Andadari et al, 2014; Alem et al, 2015; Holmes, 2010; Masatsugu and Pattanayak, 2017) and health related outcomes (Bruwen and Levine, 2012; Smith et al, 2011; Hannah et al, 2016; Lewis et al, 2017; Bensch and Peters, 2015; Yu, 2011; Yip et al, 2017; Beltramo and Levine, 2013;Lewis, 2015).

The impact of improved cook stoves and clean stoves on fuel use is a bit mixed. Whereas most studies have ascertained significant decreases in the amount of traditional fuel used, both in terms of quantities and expenditures on wood fuels (Lewis et al, 2017; Brook et al, 2016; Bensch and Peters, 2015; Beltramo and Levine, 2015; Hnyine al, 2015; Putra et al, 2017; Jain. 2014; Dresen et al, 2014; Alem et al, 2015; Holmes, 2010; Masatsugu and Pattanayak, 2017), others found the decreases were not statistically significant. Bruwen and Levin (2012) found that households that were assigned improved cook stoves in a randomized control trial in Ghana used less of fuel wood than households that used traditional stoves, nevertheless, this difference was not significant. The result was attributed to the defect of stoves used in the randomization control trial, something that has been noted by many studies on impacts of improved cook stoves, that the impact may be subjected to the quality of the stove in use. Similarly, Andadari et al (2014) did not find any significant effect on fuel use of the LPG programme in Indonesia that was aimed to replace kerosene as the main cooking fuel. The authors substantiated that the LPG programme rather than reduce energy costs, in terms of replacing kerosene, it rather increased them as households stacked fuels for cooking, which may have been attributed to the high costs of modern fuels and differentiated demands for cooking in a household.

Furthermore, the decrease in fuel use and energy cost due to use of improved and modern cooking stoves differs in different contexts. Whereas Lewis et al (2017) found that the use of biogas, LPG and electric cookers resulted into a 91 percent decrease in firewood used in Odisha, India, Brook et al, (2016) showed that the use of clean cook stoves such as LPG was associated with a daily reduction of 4.5 kilograms of biomass used by households in rural India. Moreover, Adrianzen (2013) using a randomized control trial in Northern Peruvian Andes, found that use of improved cook stoves was associated with a 46 percent decrease of firewood used despite the households that were given improved cook stoves in Northern Peruvian Andes experiencing iron frame failures. The failures were not systematically caused by inadequate usage, installation or maintenance but by faulty iron frame construction. The authors used these randomly distributed failures as instruments to identify the impact of improved cook stoves use on fuel use in Northern Peruvian Andes.

Hnyine et al (2015) and Putra et al (2017) further reiterated the impact of household's use of improved cooked stoves and modern cooking fuels on fuel use in Indonesia. Whereas Hnyine et al (2015) found significant effects on the household's energy costs which translates into a reduction in environmental degradation, Putra et al (2017) who looked at the impact of biogas technology adoption found significant reduction in firewood and a change in women's behaviour with regards to use of firewood and cooking habits. Similarly, Jain (2014) found that the adoption of biogas in India was associated with a significant fuel saving in India.

Furthermore in Africa, whereas Bensch and peters (2015), using a randomized control trial in rural Senegal substantiated the impact of improved cook stoves designed to curb firewood consumption but not smoke emissions on fuel wood consumption, Beltramo and Levine (2013) found a bit of mixed results in a randomized control trial in rural Senegal, where they examined the impact of solar ovens on several outcomes including fuel use. The authors used a phased randomized control trial, in which of the envisioned 1000 households, 465 treatments and 325 controls took part in the baseline survey. Although they did not find a significant reduction in fuel use for the whole sample, they found a reduction in fuel use for the sub sample that used solar oven to cook for households with 7 to 12 household members, who lowered their wood consumption by 14 percent.

Moreover, in the Sub-Saharan Africa, Dresen et al (2014), substantiated that Improved cook stoves could mitigate the negative effects of fuel wood harvesting and depletion of forests in Kafa, Ethiopia. Using a randomized control trial, they found that improved cook stoves reduce fuel wood consumption by 40 percent during Injera preparation, compared the traditional three stone fire, that resulted into an annual 1.28 tons of fuel wood saved per household. On the other hand, in Tanzania, Alem et al (2015) pointed that although the use of modern cooking fuels decreased the use of charcoal by 47.5 percent in urban Tanzania, but the decrease differed depending on whether the household acquired the modern cooking stoves through credit or a subsidy. Whereby households that acquired the modern cook stoves through a subsidy experienced a reduction of 54 percent in charcoal use compared to 41 percent experienced by households that were given access to credit. Similarly, Masatsugu and Pattanayak (2017) also ascertained the impact of improved cook stoves on deforestation and forest degradation in Tanzania through the decrease of fuel use.

Most papers have substantiated that, along with fuel saving, improved cook stoves and modern cooking fuel use save cooking and fuel collection time, specifically time used to collect firewood (Lewis et al, 2017; Brook et al, 2016; Bensch and Peters, 2015; Jain, 2014). Whereas Lewis et al (2017) ascertained that clean stoves that is LPG, Biogas and electric cookers are associated with substantial time savings for primary cooks, Brook et al (2016) reiterated that clean cook stoves not only reduced cooking time but also reduced fuel wood collection time in India. The authors found that the use of clean cook stoves was associated with a 160 fewer minutes for cooking and 105 fewer minutes collecting biomass fuel. Similarly, Jain (2014) stressed that the use of biogas in India was associated with time saving for women and children from drudgery of collection and carrying of firewood, cooking and cleaning of utensils as some of the impacts of biogas adoption while Bensch and Peters (2015) ascertained the impact of improved cook stoves and clean cook stoves respectively on cooking time and fuel collection time in Burkina Faso.

Closely linked to the impact on fuel use is the impact on health. The reduction of biomass fuel use in a household is associated with a reduction of indoor air pollution, which results in a reduction of self-reported acute respiratory and other health related outcomes associated with cooking such as burning eyes (Bruwen and Levin, 2012; Smith et al, 2011; Lewis et al, 2017; Bensch and Peters, 2015; Yu, 2011; Hannah et al, 2016). The results of impacts of improved cooked stoves and modern cooking fuels on health are also mixed, whereas some studies have found significant reduction on incidences of health-related outcomes (Bruwen and Levin, 2012; Smith et al, 2011; Lewis et al, 2017; Bensch and Peters, 2015) others have not found any significant effect (Hannah et al, 2016; Beltramo and Levine, 2013).

Bruwen and Levin (2012) found significant impacts of improved cook stoves use on self-reported symptoms associated with cooking such as burning eyes and respiratory symptoms such as chest pains and runny nose in Ghana. Similarly, Smith et al (2011) found significant reductions in health-related outcomes in Guatemala associated with household's use of improved cook stoves. Using a randomized control trial, 534 households with a pregnant woman or an infant were assigned to treatment and control groups, with 269 in the treatment group and 265 in the control group, the authors ascertained the impact of improved cook stoves on childhood pneumonia. The authors found a significant reduction in the field work assessed pneumonia, physician assessed pneumonia and radiological confirmed pneumonia. Nevertheless, the results were not significant for children under 18 months of age.

Lewis et al (2017) reiterated the role of clean cook stoves (LPG, Electric and biogas) in reducing indoor air pollution and incidence of acute respiratory symptoms in India. The authors found that the use of clean coking stoves was associated with a 72 percent reduction in particulate matter, 78 percent reduction in PAH levels and significant reduction in water soluble organic carbon and nitrogen in the household. The authors substantiated a significant reduction in visit to the hospital due to acute respiratory infection and reduced diastolic blood pressure. These results were attributed to persistent use of clean cook stoves. Furthermore, Bensch and Peters (2015) pointed out that due to reduced firewood consumption by households, improved cook stoves also led to a reduction in smoke exposure and consequently smoke related disease symptoms. The results were attributed partly to behavioral change by households due to cooking outside of the household.

Similarly, Yu (2011) using comprehensive data from the world bank and the government of China reiterated the fact that behavioral intervention coupled with stove interventions had significant impacts in acute respiratory infections for children aged five and under in rural China. The authors used both difference in difference and matching models to ascertain the impact of stove and behavioral intervention in reducing indoor air pollution from cooking and heating stoves and consequently the incidence of acute respiratory infection in children aged five and under.

Nevertheless, Hannah et al (2016) found results contrary to what others had found with regards to reductions in acute respiratory symptoms in India. Using a randomized control trial in India, the authors found that although smoked exposure initially falls, the effect disappears in year two. They thus generally did not find any significant changes across health outcomes or greenhouse emissions. The study pointed out that human behavior may undermine the potential outcomes of improved cook stoves in the real world, as most households were found to have used the improved cook stoves irregularly and inappropriately. Similarly, Beltramo and Levine (2013) did not find any significant reductions in exposure to carbon monoxide nor self-reported respiratory symptoms such as coughs and sore throats.

Overall, our review of literature depicts positive impacts of improved and clean cook stoves on the household welfare, specifically with regards to wood fuel consumption and health. Nevertheless, there are very few studies that look at the impacts of household cooking energy transitions in Africa, more prominently Sub-Saharan Africa. As the impacts of such transitions differ in different contexts due to behavioral aspects and cooking habits, it is imperative to have more papers providing evidence of such impacts in Africa, specifically Sub-Saharan Africa. Moreover, the few studies in Africa have mostly studied the impact of improved cook stoves (Yip et al., 2017; Bensch and Peters, 2015; Bruwen and Levin, 2012), very few studies have looked at the impact of clean cookstoves (LPG, electrical cookers, Biogas and solar cookers) on the household welfare (Beltramo and Levine, 2013; Alem et al., 2015). Although studies have cited liquidity constraints as a hindering factor in adoption of clean stoves (Alem et al., 2014; Alem et al., 2015), it’s imperative to provide scientific evidence for their impacts, to advocate for policies to relax liquidity and other existing constraints for their adoption. Thus, our study adds to the few literatures in Africa, specifically the Sub-Saharan Africa by looking at the impact of household use of modern cooking on the household welfare indicators in Tanzania.

There have been a few studies that have looked at the impact of modern cooking stoves in Tanzania (Masatsugu and Pattanayak, 2017; Alem et al., 2015; Bwenge, 2011; Holmes, 2010). Nevertheless, very few have done proper quantitative impact analysis (Alem et al., 2015; Masatsugu and Pattanayak, 2017), while others have only investigated these impacts qualitatively (Bwenge, 2011; Holmes, 2010). This paper wants to add to the few thorough impact evaluations within the confined theory of change and methodological assumptions in Tanzania. Whereas Masatsugu and Pattanayak (2017) looked at the impact of improved cook stoves on wood fuel indirectly, by looking how the REDD+ interventions increased the adoption of improved cook stoves in the tropics, including Tanzania, Alem et al (2015) went further and looked at how relaxing liquidity constraints improves adoption of LPG stoves and impacts Charcoal consumption in Tanzania. Our study wants to provide more evidence on the impact of clean cook stoves on charcoal expenditures and other related household energy expenditures in Tanzania and go a step further and look at any suggestive impact of clean cook stoves on respiratory health of children under five years of age in Tanzania.

2.2 Impact of electrification on household welfare indicators

The impacts of household electrification on the various welfare indicators differ in various places depending on the context and the success of the impact evaluation exercise. Studies have covered various contexts in different places in the world including Asia (Khandker et al, 2012; Arraiz and Calero, 2015; Samad et al, 2013; Aguirre, 2014; Van de walle et al., 2015; Daso and Fernandez, 2015), Africa (Grimm et al, 2016; Bensch et al, 2011; Furakawa, 2014; Aevarsdottir et al., 2017), South and Central America (Arraiz and Calero, 2015; Barron and Torero, 2017). The methodologies used range from experimental methods (Barron and Torero, 2015; Grimm et al, 2016; Furakawa, 2014) and most prominently, non-experimental methods such as propensity score matching, Instrumental variables, Fixed effects panel models and difference in difference (Arraiz and Calero, 2015; Samad et al, 2013; Khandker et al, 2012; Bensch et al, 2011; Aguirre, 2014; Arraiz and Calero, 2015).

There is a vast of literature on the impacts of electrification on various welfare indicators. These include impacts on Time allocation (Grimm et al, 2016; Arraiz and Calero, 2015; Samad et al, 2013; Khandker et al, 2012; Bensch et al, 2011; Barron and Torero, 2017; Aguirre, 2014; Furakawa, 2014; Aevarsdottir et al.,2017), Employment and labor supply (Barron and Torero, 2015; Daso and Fernandez, 2015; Van de Walle et al, 2015), Wages, earnings and income (Bensch et al, 2011; Arraiz and Calero, 2015; Barron and Torero, 2015; Aevarsdottir et al.,2017), Consumption and expenditure (Van de walle et al., 2015; Bensch et al, 2011; Arraiz and Calero, 2014; Samad et al, 2013; Grimm et al, 2015), schooling (Van de Walle et al, 2015; Khandker et al, 2012; Arraiz and Calero, 2014; Furakawa, 2014) and health (Samad et al, 2013; Barron and Torero, 2017; Aevarsdottir et al.,2017). This paper will further look to substantiate the impact of electrification on energy expenditures, education outcomes and health in Tanzania.

One of the immediate impacts of household electrification is the impact on energy expenditures. This is because households adopt electricity primarily for lighting and thus electricity directly replaces other sources of lighting like kerosene, Candles and batteries, thus impact expenditures on such sources and expenditures on energy at large. The impact of electrification on energy expenditures is a bit mixed whereas some studies find significant increases in energy expenditures (Bensch et al., 2011; Samad et al., 2013; Van de walle et al., 2015) other studies find significant decreases in energy expenditures (Arraiz and Calero, 2014; Grimm et al, 2016; Karumba and Muchapondwa, 2018). Although Bensch et al., (2011) found a marginal significant increase in energy expenditures in Rwanda using propensity score matching techniques, they pointed out that the intensive use of lighting and electricity for other electrical appliances may outweigh the efficiency of the household's switch from traditional sources to electricity. Moreover, the authors reiterated that when regional differences were considered, there were no significant differences in energy expenditures between the connected households in access regions and the non-connected households in non-access regions. Similarly, Van de walle et al., (2015) substantiates the significant increase in energy expenditures due electrification in India. Using a long panel data set, the authors reiterated that one of the long-term impacts of electrification in India was significant increases in household total expenditure, particularly for food and fuel.

Studies that have found significant decreases in fuel expenditures, not only have they pointed out a decrease in fuel expenditures (Grimm et al, 2016) but also specific expenditures on traditional fuels used for lighting, such as kerosene, candles and batteries (Arraiz and Calero, 2014; Karumba and Muchapondwa, 2018). Grimm et al., (2016) substantiated that electrification has had a positive impact on the household budget with regards to a decrease in cost per lighting hour, which was calculated by dividing expenditures on lighting fuels (kerosene, candles, batteries) by the number of lighting hours consumed. The authors concluded that such savings translated to more lighting hours consumed from electrification from solar PV. Moreover, they observed an approximately 70 percent decrease in kerosene expenditures. Similarly, Karumba and Muchapondwa (2018) found that households connected to electricity spent less on kerosene per month compared to households without electricity connections. Furthermore, Arraiz and Calero (2014) also reiterated the decrease in expenditure for candles, batteries and firewood due to electrification, nevertheless they did not find any significant effect on total fuel expenditures.

Moreover, electrification has been linked with time allocation changes by households. Nevertheless, the impact of electrification on time allocation is a bit mixed. Whereas Grimm et al (2015) finds no effect on time allocation of household members in Rwanda, other studies find significant effects (Arraiz and Calero, 2014; Samad et al, 2013; Khandker et al, 2012; Bensch et al, 2011; Bernard and Torero, 2015; Barron and Torero, 2015; Aguirre, 2014; Furakawa, 2014). Arraiza and Calero (2014) found significant effects of electrification on the time spent awake, as members of the household spend more time awake. Furthermore, they stress that electrification decreases the time women spend on agricultural activities and increase the time they spend on household activities. This is one of the key mechanism through which electrification impacts time allocation and hence household welfare as reiterated by Bonan et al., (2016), with the switch to household activities/non-agricultural activities which electricity contributes to develop like small businesses and firm's investment in electrical appliances that need non-agricultural labor.

This was further reiterated by Barron and Torero (2015) who found significant increases in non- farm employment and home businesses specifically for women in El-Salvador. Nevertheless, Bernard and Torero (2015) found no significant short run effects of rural electrification on time spent on income generating activities. Similarly, Van da Walle et al., (2015) found significant time allocation from casual labor work to regular wage jobs and agricultural self-employment for men. Marginal effects were found for women. Furthermore, they found a significant increase in hours worked for men and their likelihood of having more than one job. Such time allocation effects may also materialize due to time saved from traditional energy connected activities and extending the working day well beyond the sunset (Bonan et al., 2016).

Linked to time allocation due time saved and an elongated working day, is children's study hours. Samad et al (2013) found significant increases in children study time in Bangladesh and time for fuel collection for women. Not only did other studies find significant increases in children's study time but also, they found significant increases in time used by children in educational activities and household chores (Khandker et al, 2012; Bensch et al, 2011; Bernard and Torero, 2015; Barron and Torero, 2015; Aguirre, 2014; Furakawa, 2014). Nevertheless, other studies have found negative significant effects of electrification on children's study hours, citing the fact that children may use more of their time to watch television instead of studying (Karumba and Muchapondwa, 2018).

Closely linked to the impact on children's study hours is the impact on education attainment and school performance (Van de Walle et al., 2015; Khandker et al, 2012; Arraiz and Calero, 2014; Furakawa, 2014). The results have also been mixed with regards to different contexts. Whereas most studies have substantiated a positive effect of electrification on education attainment (Van de Walle et al., 2015; Khandker et al, 2012; Arraiz and Calero, 2014), other studies have found negative significant effects on school performance and education attainment (Furakawa, 2014; Squires, 2015). Inferior quality of lighting, increase in children employment and adult employment that drives children to stay at home to compensate for parents going for work have been cited as key drivers for such negative impacts (Furakawa, 2014; Squires, 2015).

One of the least studied but key area of inquiry is the impact of electrification on fertility and health related outcomes such as respiratory disease symptoms. Barron and Torero (2017) substantiated the impact of electrification in reduction of indoor air pollution caused by traditional fuels for lighting and consequently a reduction in acute respiratory symptoms among children under six in El Salvador. Similarly, Samad et al., (2013) found significant reduction in respiratory disease symptoms for women in Bangladesh. On the other hand, studies have pointed out the impact of electrification on fertility. A 2008 World Bank study using cross sectional data from Ghana, Peru, the Lao People's Democratic Republic and the Philippines substantiated a negative relationship between electrification and fertility due to improved access to information technologies (Arraiz and Calero, 2014)

Our study wants to add to the literature of impacts of household's use of electricity by investigating these impacts in the context of Tanzania. Whereas, a few studies have made an attempt to study the impact of electrification on a vast of outcomes, to our knowledge, our study is among the first and few studies in Tanzania, that makes an attempt to comprehensively study the impact of electrification on a number of outcomes including energy expenditures, schooling outcomes, time use and add to few studies that look at the impact of electrification on health and fertility. Although Aevarsdottir et al, (2017), made a similar attempt in Tanzania, their study focused on the impacts of electrification form solar lamps in the rural areas. Our study looks at the use of electricity (both grid and off-grid) and studies its impacts not only for the rural area, but rather for the whole sample and sub samples in the urban and rural areas, thus gets the differential of impacts in different contexts within the country.

3. Methodology

3.1 Theory of change

3.1.1 Modern cooking fuels

The use of modern cooking fuels (LPG and Electricity) is expected to have a direct impact on household energy expenditures. We expect the use of modern cooking fuels to replace the traditional cooking fuels, which can either be a total replacement that is a household uses modern cooking fuels alone or a partial replacement, which entails a household using both modern and traditional cooking fuels. We expect that households that use modern cooking fuels would on average spend less on wood fuels compared to households that use wood fuels only, (Brooks et al, 2016; Bensch and Peters, 2015; Beltramo and Levine, 2013; Adriazen, 2013). As our analysis of the impact of modern cooking fuels is more centred in urban and peri-urban areas of Tanzania, where the prominent wood fuel used is charcoal, we expect on average a decrease in charcoal expenditures for households that use modern cooking fuels. Thus, in the long run this translates in lower quantities of charcoal consumed and thus reduce the pressure on forests.

The use of modern cooking fuels potentially reduces health associated risks of using wood fuels such as firewood and charcoal, (Burwen & Levine, 2012). The world health organization has stressed on the severe health consequences of indoor air pollution caused by the use of wood fuels (firewood and Charcoal), diseases like pneumonia and heart diseases are attributed to indoor air pollution, (Ezzati and Kammen, 2001). The adverse effects of indoor air pollution are more severe for women and children who spend most of their time around the kitchen. As per the investigation of our study, we expect households that use modern cooking fuels to have less number of children aged five years and below that suffer from self-reported acute respiratory symptoms such as cough and shortness of breath.

3.1.2 Electrification

Once a household is connected to electricity, the immediate impact is observed in its expenditures, specifically its energy expenditures. Furthermore, our theory of change premise with regards to electrification also expect impact on education, time use and health. We expect a decrease in the household energy expenditure, specifically on kerosene expenditures. This is because electricity will first and foremost replace other lighting fuels, most prominently kerosene which is being used for lighting by 21 percent and 27 percent of the urban and rural households respectively in Tanzania. Electrified households are expected on average to spend less on kerosene compared to non-electrified households, (Samad et al., 2013; Karumba and Muchapondwa, 2017; Grimm et al, (2015)).

Moreover, electrification impacts household welfare through changes in time allocation of household members. This results in welfare improvement through mechanisms like time saved from energy related activities (cooking and fuel collection), increase in the work day and a switch from agricultural to non-agricultural activities, (Bonan et al, 2016). Our paper considers the later mechanism of the switch from agricultural activities to non-agricultural activities that have resulted due to electrification. This may be in the form of small businesses and firms, which demand non-agricultural labour, (Bonan et al, 2016). We expect household members in electrified households to spend more time in non-agricultural activities compared to those from non-electrified households.

The quality of lighting from electricity is expected to increase children study hours. We expect that children in electrified households to study for longer hours in the evening than those in non-electrified households. Linked to longer hours of study, is education attainment and school performance. Children in electrified households are expected to go further in terms of schooling, both in terms of passing and study years, (Khandker et al, 2012). We thus expect that students in rural and urban areas in electrified households to be more educated and reach higher levels of schooling.

As electrification is expected to replace traditional sources of light specifically kerosene, which produces fumes that not only pollute the household but also lead to health problems, we expect electrified households to have low concentration of indoor air pollution and thus lead to a reduction in acute respiratory symptoms infections in the households, especially for children under the age of five, (Barron and Torero, 2017). Furthermore, linked to health impacts, is the impact on fertility. Studies have shown that electrification may be attributed to decreased fertility due to improved access to family planning information. We hypothesize that as electrification increases the use of appliances like radios, mobile phones and televisions, families in electrified households are more likely to get information on family planning and hence increase the number of women using modern family planning methods and lead to a decline in fertility, (Arraiz and Calero (2015), IEG (2008). Peters and Vance (2011)). Table 1 in the appendix summarizes the outcomes of interest in the study and how they are measured.

3.2 Identification Strategy

3.2.1 The theory of Impact evaluation and Propensity score matching

We adopt the counter factual framework pioneered by Rubin (1974) and since adopted by many in both statistics and econometrics, including Rosenbaum and Rubin (1983), Heckman (1992, 1997), Imbens and Angrist (1994), Heckman, Ichimura and Todd (1997) and Angrist (1998) (Wooldridge, 2002). We adopt this approach in conducting the two impact exercises that is the impact of a household's use of modern cooking fuels and the impact of household electrification on household welfare indicators in Tanzania. Our impact inference hinges on speculation of how a household would have performed had it not received the treatment. The Roy (1951) and Rubin (1974) model formalizes the evaluation of this problem in a potential outcome approach.
As per our study, the main pillars of this model are households, treatment (our treatments of interest being "adoption of modern cooking fuels" and "household electrification") and potential outcomes (energy expenditures, time use, education and health). Our treatments are binary in nature. As stipulated in Caliendo and Kopeinig (2008) for a binary treatment, the treatment indicator D_i for household i equals one if a household receives a treatment and zero otherwise. $Y_i(D_i)$ defines the potential outcomes for each household i, where i = 1, 2, 3…, N. Where N denotes the total population. The treatment effect for household i can be written as:

$$\tau_i = Y_i(1) - Y_i(0) \quad (1)$$

Nevertheless, as we can only observe one of the potential outcomes, estimating the household outcomes τ_i is not possible. Accordingly using a counter factual outcome, which stipulates the unobserved outcome, we concentrate on estimating average treatment effects.

As most evaluation studies and befitting our study we estimate the average treatment effect on the treated (ATT), defined as;

$$\tau_{ATT} = E(\tau|D = 1) = E[Y(1)|D = 1] - E[Y(0)|D = 1] \qquad (2)$$

The counterfactual mean for the treated $E[Y(0)|D = 1]$ is not observed. Thus, the fundamental problem becomes the choice of a proper substitute for it to estimate the average treatment effect on the treated (ATT). It's tempting to use the mean outcome of the untreated individuals $[Y(0)|D = 0]$, nevertheless in a non-random experiment like our case, this may not be feasible because it's likely that the factors that determine the treatment decision also determine the outcome. Hence even without the treatment the outcomes of households in treatment and comparison groups would differ even in the absence of treatment leading to a self-selection bias. Rewriting equation (2),

$$E[Y(1)|D = 1] - E[Y(0)|D = 0] = \tau_{ATT} + E[Y(0)|D = 1] - E[Y(0)|D = 0] \qquad (3)$$

The equation (3) and equation (2) only differ by the selection bias component. The true parameter τ_{ATT} is only identified if:

$$E[Y(0)|D = 1] - E[Y(0)|D = 0] = 0 \qquad (4)$$

The only way to ensure this is by random assignment of the treatment. Social experiments using random control trials ensure of this, but non-experimental studies like our own need methodologies that invoke certain assumption to solve the selection bias problem. Our study taking into consideration the type data available and the question we intend to answer will make use of propensity score matching based techniques to reduce the selection bias problem.

3.2.2 Propensity Score Matching

Rosenbaum and Rubin (1983) define a propensity score as the conditional probability of receiving a treatment given pre-treatment characteristics:

$$p(X) \equiv \Pr(D = 1|X) = E(D|X) \qquad (5)$$

Where X is a vector of pre-treatment characteristics. Rosenbaum and Rubin (1983) proved that, if the treatment assignment is random within cells defined by X then it's also random within cells defined by $p(X)$. Hence comparing means outcomes of control and comparison group at the values of the score yields unbiased estimates. The unbiased average treatment on the treated, given the propensity score can be estimated as

$$\tau_{ATT}^{PSM} = E_{(P(X)|D=1)}\{E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0, P(X)]\} \qquad (6)$$

Propensity score matching hinges on the two main assumptions for the estimation of unbiased estimates. The first assumption is the conditional independence assumption that stipulates that for a given a set of observable covariates X, potential outcomes are independent of treatment assignment. This is a very strong assumption which most of the times is only justified by the quality of the data at hand. Thus, based on a propensity score this condition can be written as:

$$Y(0), Y(1) \perp D|P(X) \qquad (7)$$

The second assumption is the common support. This assumption rules out the phenomenon of perfect predictability. Thus, households with the same propensity scores have a positive probability of being both in treatment and comparison group, (Caliendo & Kopeinig, (2008); Heckman et al, (1999)):

$$0 < P(D = 1|X) < 1 \qquad (8)$$

Based on the mentioned assumptions, propensity score matching reduces the bias of the difference in means of outcomes over the common support.

3.3.3 Implementation of the propensity score matching

The implementation of propensity score matching as explained in detail in Caliendo and Kopeining (2008) entails the following steps;

Estimating the propensity scores

This entails choosing the model to be used for the estimation of the propensity scores and the variables to be included in the model. Any choice discrete model can be used, that is a logit or probit. These are preferred over the linear probability models due to the well-known shortcomings of the linear probability model, (Caliendo and Kopeining, 2008). When the treatments are binary as in our case, the probability of being treated vs. the probability of not being treated estimated by the logit or probit models are usually similar. This paper uses the logit model to estimate the propensity scores. The logit model that a household is treated is a linear function of X (observable characteristics):

$$logit(\theta_i) = F(X'\alpha) = X_i'\alpha \quad (9)$$

Where α is a vector of coefficients and F(.) is the cumulative density function of the logistic distribution. The propensity scores are generated from the predicted probability based on model (9). The probability that a household is treated is given by:

$$\theta_i = \frac{exp\{X_i'\}}{1 + exp\{X_i'\}} \quad (10)$$

According to Caliendo and Kopeining (2008) matching hinges on choosing the most credible set of observables X, as omitting important variables can increase bias in resulting estimates. It's advised to include only variables that simultaneously influence the treatment decision and outcome variables. Thus, this study on taking that into consideration, chose variables to be included in the participation models that are supported by economic theory and previous research on impacts of household energy transition.

Choosing a matching Algorithm

After the estimation of the propensity scores, one must choose the appropriate matching procedure to contrast the outcome of treated households with outcomes of comparison households. The different matching algorithms differ in how the neighbourhoods for treated individuals are defined and the common support problem is handled, (Caliendo and Kopeining, 2008). Choice between different algorithms entails a trade-off between bias and efficiency. There are five matching algorithms that we can chose from, these include the Nearest Neighbourhood matching, calliper and radius matching, Stratification and interval matching, Kernel and local linear matching and finally is weighting on propensity scores. This study makes use of the Kernel matching algorithm.

The Kernel matching algorithm

The kernel matching behaves as a weighted regression of counterfactual outcomes on an intercept with weights given by the kernel weights, (Caliendo and Kopeining, 2008). Weights are allocated to each control within a predefined range (band-width) based on their proximity to the treated subjects, (Karumba and Muchapondwa, 2018). A symmetric, nonnegative and unimodal kernel places higher weight on controls close in terms of propensity scores of the treated group and a lower weight on more distant controls, (Caliendo and Kopeining, 2008). Study chose to use the kernel matching to use as much information as possible from the data and thus achieve a lower variance in the process. To reduce the possibility of bad matches in both the impact evaluation exercises we use a bandwidth of 0.06 or below so as to balance the trade-offs between variance and bias, (Caliendo and Kopeining, 2008). Furthermore, our estimation is restricted to the common support region. The kernel matching estimator is given by:

$$\tau^{k} = \frac{1}{N^{T}} \sum_{i \epsilon \mathrm{T}} \left\{ Y_{i}^{\mathrm{T}} - \frac{\sum_{j \epsilon C} Y_{j}^{C}\, G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \epsilon C} G\left(\frac{p_k - p_i}{h_n}\right)} \right\} \tag{11}$$

The G(.) is the kernel function. Under standard conditions:

$$\frac{\sum_{j \epsilon C} Y_{j}^{C}\, G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \epsilon C} G\left(\frac{p_k - p_i}{h_n}\right)}$$

is a consistent estimator of the counterfactual. We estimated bootstrap standard errors. As the kernel based matching estimator is asymptotically linear, the bootstrap provides a valid inference for the standard errors, (Arraiz and Calero, 2015; Abadie and Imbens, 2008).

The matching quality

As the matching is done based on propensity scores it's advised to check the quality of matching and assess if the matching procedure is able to balance the distribution of all the relevant variables in both the control and treatment group, (Caliendo and kopeining, 2008). All the approaches that assess the matching quality try to test if there any significant differences remaining between the treated and control groups after the matching, (Caliendo and kopeining, 2008). This is in line with the theorem suggested by Rosenbaum and Rubin (1983) that after conditioning on the propensity scores, additional conditioning on X should not provide new information about the treatment decision. Any dependence of the treatment decision on X after matching suggests a misspecification in the model used to estimate the propensity scores or a failure of the conditional independence assumption, (Caliendo and kopeining, 2008; Smith and Todd, 2005).

There are several approaches of assessing the matching quality, these include the standardised bias, which for any given covariate it's defined as the difference in the sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups, (Caliendo and kopeining, 2008; Rosenbaum and Rubin, 1985). The standardised bias before and after matching are given by:

$$SB_{before} = 100.\frac{(\bar{X}_1 - \bar{X}_0)}{\sqrt{0.5(V_1(X) + V_0(X)}} \tag{12}$$

$$SB_{after} = 100.\frac{(\bar{X}_{1M} - \bar{X}_{0M})}{\sqrt{0.5(V_{1M}(X) + V_{0M}(X)}} \tag{13}$$

Where $\bar{X}_1$ and V_1 is means and variance respectively of the treatment group. $\bar{X}_0$ and V_0 is the mean and variance respectively for the control group before matching. Analogously $\bar{X}_{1M}$ $\bar{X}_{0M}$ V_{1M} and V_{0M} are corresponding values for the matched samples. Thus, one of the common approaches in evaluation studies in assessing matching quality. In most studies a bias reduction below 3% or 5% is deemed sufficient. (Caliendo and kopeining, 2008). The other similar approach is a simple t-test, which uses a two-sample t-test to check if there are significant differences in covariates of means of the treated and control groups before and after matching, we expect to have no significant differences in covariates between the treated and control groups after matching if the matching in propensities was successful. The stratification test suggested Dehejia and Wahba (1999, 2002), implemented analogously as a simple t-test but the t-tests is conducted within strata based on the estimated propensity scores.

Sianesi (2004) suggested the use of the joint significance of the covariates and pseudo-R^2. The approach requires a re-estimation of the propensity score on the matched sample and compare the pseudo-R^2 after matching and before matching. After matching there shouldn't be any systematic differences between the groups and thus the pseud-R^2 should be very low. More over an F-Test of the joint significant of the regressors should be rejected before matching and should not be rejected after matching. (Caliendo and kopeining, 2008). This study uses the standardised bias, the t-test and the Joint significance and Pseudo- R^2 to assess the matching quality.

Sensitivity analysis

As propensity score matching estimates treatment effects based on the conditional independence assumption that is conditioning on observable characteristics, if there are unobservable variables which simultaneously affect treatment assignment and the outcome variable a hidden bias may arise, (Caliendo and kopeining, 2008). The magnitude of this selection bias cannot be estimated with non-experimental data. To address this problem Rosenbaum (2002) proposed a bounding approach that tries to check if inference may be altered by unobservable factors. As Caliendo and kopeining (2008) put it, the bounds determine how strongly an unmeasured variable may influence the selection process and thus, undermine the implications of the matching analysis. If the participation probability is:

$$P(X_i) = P(D_i = 1|X_i) = F(\beta X_i + \gamma\mu_i) \tag{14}$$

Where X_i are observed characteristics for household i, μ_i is the unobserved variable and γ is the effect of μ_i on the participation decision of the household. If a study is free of hidden bias, γ will be zero and thus the participation probability of the household. The presence of a hidden bias means two households with similar observable characteristics may have different chances of receiving treatment, (Caliendo and kopeining, 2008). Rosenbaum (2002) shows that the odds ratio of the odds that two matched households i and j receive treatment imply the following bounds:

$$\frac{1}{e^{\gamma}} \leq \frac{P(X_i)\left(1-P(X_j)\right)}{P(X_j)\left(1-P(X_i)\right)} \leq e^{\gamma} \quad (15)$$

Where e^{γ} measures the extent to which a study has deviated from a study that is free of hidden bias, (Caliendo and kopeining, 2008; Rosenbaum, 2002).

3.3.4 The Data

The study makes use of two data sets that is the 2014/2015 Tanzania national panel survey and the 2015/2016 Tanzanian Demographic and health survey and malaria indicator survey. We used two data sets to accomplish the objectives at hand. Specifically, the 2014/15 national panel survey was used to study the impact of household adoption of modern cooking fuels and Household electrification on non-health outcome variables while 2015/2016 Tanzanian Demographic and health survey and malaria indicator survey to ascertain the impacts on health-related outcome variables.

The 2014/2015 Tanzania national panel survey is the fourth wave in the series of nationally representative household panel survey that collects a data on various social economic characteristics, (NBS, 2016). The survey collected data at the individual, household and community level. The survey used four survey instruments; the household questionnaire, the agriculture questionnaire, the livestock/fishery questionnaire and a community questionnaire. The 2014/2015 wave was a refreshed wave for the household panel survey series, using the 2012 Tanzanian population census as its master sample frame. The wave used a revised sample, where only a sub-sample of the National panel survey (NPS) was selected to continue as an extended panel and an entirely new sample "refreshed sample" was sampled to represent the national and sub-national domains, (NBS, 2016). The wave used a multi-stage clustered sampling design, with four analytical strata; Dar-es-salaam, other urban areas in mainland, rural mainland and Zanzibar. Clusters were chosen at random from each stratum, with the probability of selection proportional to their population size. From the selected primary sampling units, 8 households were chosen at random from each cluster.

On the other hand, the 2015/16 Tanzanian Demographic and health survey and malaria indicator survey is a sixth in the series of demographic and health surveys conducted in Tanzania. Its main objective was to obtain up to date information on demographic and health indicators including among others fertility, family planning and acute respiratory health for children under 5, which are of prime interest for this study. The survey adopted a two-stage sampling design designed to provide estimates that are country representative that is urban and rural areas in Tanzania mainland, and for Zanzibar, (NBS, 2016). Nevertheless, for specific indicators like contraceptive use the sampling design allowed the estimation for indicator for all the 30 regions in the country. The first stage of the sampling sampled clusters and the second stage selected 22 households from each sampled cluster and resulting in a sample of 13,376. The 2012 Tanzanian population census was used as the master sampling frame. The survey used four survey instruments: household questionnaire, women's questionnaire, man's questionnaire and biomarker questionnaire.

4. Results and Discussions

The study investigated the impact of household energy transition both in terms of cooking and lighting fuels. This section presents the results in two sections. The first part will present the results on the impact of household use of modern cooking fuels on household welfare indicators and the subsequent section will present and discuss results of the impact of household use of electricity for lighting on household welfare indicators.

4.1 The Impact of modern cooking fuels on household welfare

4.1.1 Data description

The use of modern cooking fuels in Tanzania is still very low. As seen in Table 2 in the appendix, only 3.34 percent of households in the used sample use modern cooking fuels (LPG and Electricity), that is 112 households out of the 3344 households. The use of modern cooking fuels is more prominent in urban areas, with about 8.3 % of the households using modern cooking fuels. The use of modern cooking fuels in rural areas is near to non-extent, with only three households (0.17%) out of the 1776 rural households sampled for the 2014/15 national panel survey using modern cooking fuels. Based on the prominence of use of modern cooking fuels, our analysis was restricted to the full sample (Country level) and the urban sample.

As stated earlier, we used the 2014/15 Tanzania national panel survey to investigate the impact of household's use of modern cooking fuels on household's energy expenditures. The study used 3344 and 1094 households for the country (full sample) and the urban areas (urban sample) analyses respectively. Before matching, on the basis of the simple t-test, the treated and control households used in the full sample analysis were statistically similar in only three out of the eight characteristics used as balancing covariates in the full sample analytical model while in the urban sample the households were similar in only two of the nine characteristics used as balancing covariates in the urban sample analytical model (see table 3 and 4 in the appendix).

Similarly, the study used 2015/16 Tanzanian Demographic and health survey and malaria indicator survey to study the impact of household modern cooking fuel use on health for children that are five years of age and under and fertility for women. The study used 5557 and 1522 households for the country (full sample) and urban areas (urban sample) analyses respectively. Before matching, on the basis of the simple t-test, the treated and control households used in the full sample analysis were statistically similar in only three out of the eleven characteristics used as balancing covariates in the full sample analytical model while in the urban sample the households were similar in only two of the seven characteristics used as balancing covariates in the urban sample analytical model (see table 5 and 6 in the appendix). The statistical difference in the covariate means before matching in both data sets is largely expected (Caliendo and Kopeining, 2008), and thus comparing these group's outcomes of interest will result in biased results as these characteristics may simultaneously influence a household's treatment status and the outcomes of interest. To reduce such biases the study used propensity score matching to ascertain the best counterfactuals for our analyses.

4.1.2 Estimating the propensity scores

The study estimated the propensity scores for the individual samples in the respective data sets used. The study used the logit model to estimate the propensity scores. Table 7 and 8 in the appendix show the logit models used to estimate the propensity scores for households used for the impact of household use of modern cooking fuels on expenditures and health related outcomes respectively. The covariates used in the models were included based on the theory and literature of household cooking fuel choice. Moreover, as advised in Caliendo and Kopeining (2008), only those variables that simultaneously affect the treatment status of the households and the outcomes variables of interest were included in the models. Household income, education level of the household head, age of the household head, household's ownership of various assets like a house, mobile phones and televisions were among the variables that were included in the logit models used to estimate the propensity scores for the full sample and the urban samples of the respective data sets used for the analysis of the impact of household's use of modern cooking fuels on household welfare indicators in Tanzania.

4.1.3 The common support and matching quality

The study then checked if the overlap condition was satisfied. Furthermore, the matching quality was assessed for the sub samples, within the individual data sets that were used for the analysis of the impact of household use of modern cooking fuels on energy expenditures and health related outcomes respectively. Firstly, the common support and the matching quality was assessed for the fourth wave of the Tanzania national panel data set, used for the analysis of the impact of household use of modern cooking fuels on household energy expenditures. As the analysis was done for both the full sample and the urban sample within the data set, we accordingly start with the full sample assessment. The easiest way to assess the common support is by looking at the distribution of propensity scores of the treatment and the control group. The distribution of the propensity scores and the common support region for the full sample analysis are presented in figure 1(see in the appendix). Out of the 3344 households used for the full sample analysis, 3340 were on the common support. The four households that were not on the common support were from the treatment group, which constituted of 112 households. The kernel (Epanechnikov) matching with a bandwidth of 0.06, is the one that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores, whereby almost all the covariates after matching had standardized biases of 5% and below (See Table 3 in the appendix) and the mean standardized bias stood at 3.1%. Similarly, for the urban sample, the common support and the distribution of the propensity scores are presented in figure 2 (see in the appendix). Out of the 1094 households used for the urban sample analysis, 1081 were on the common support. The thirteen households that were not on the common support were from the treatment group, which constituted of 91 households. The kernel (Epanechnikov) matching with a bandwidth of 0.06, is the one that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores, whereby almost all the covariates after matching had standardized biases below 5% (See Table 4 in the appendix) and the mean standardized stood at 2.7%. Furthermore, the Pseudo-R2 after matching for both the sub samples (see Table 9 in the appendix) was considerably lower, meaning that there are no systematic differences in the distribution of the covariates between the treatment and the control groups of the respective samples. This is further ascertained by the joint significance test of the covariates after matching (see Table 9 in the appendix).

Secondly, the common support and the matching quality was assessed for the 2015/16 Tanzania demographic household survey, used for the analysis of the impact of household use of modern cooking fuels on health and fertility. Similarly, the analysis was done for the full sample and the urban sample within the data set. Starting with the full sample, the study assessed the common support by looking at the distribution of propensity scores of the treatment and the control group. The distribution of the propensity scores and the common support region for the full sample analysis are presented in figure 3 (see in the appendix). Out of the 5557 households used for the full sample analysis, 5,555 were on the common support. The two households that were not on the common support were from the treatment group, which constituted of 87 households. The kernel (Epanechnikov) matching with a bandwidth of 0.02, is the one that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores, whereby almost all the covariates after matching had standardized biases of 5% and below (See Table 5 in the appendix) and the mean standardized bias stood at 2%. Similarly, for the urban sample, the common support and the distribution of the propensity scores are presented in figure 4 (see in the appendix). Out of the 1522 households used for the urban sample analysis, 1,519 were on the common support. The three households that were not on the common support were from the treatment group, which constituted of 75 households. The kernel (Epanechnikov) matching with a bandwidth of 0.02, is the one that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores, whereby almost all the covariates after matching had standardized biases below 5% (See Table 6 in the appendix) and the mean standardized stood at 3%. Furthermore, the Pseudo-R2 after matching for both the sub samples (see Table 9 in the appendix) was considerably lower, meaning that there are no systematic differences in the distribution of the covariates between the treatment and the control groups of the respective samples. This is further ascertained by the joint significance test of the covariates after matching (see Table 9 in the appendix).

4.1.4 The Treatment effect

This section presents the discussion on the effect of household's use of modern cooking fuels on the household's welfare, whereby as discussed beforehand, our treatment variable was an indicator variable equal to one if a household uses modern cooking fuels (LPG and/electricity). This section will be divided into two parts, whereby the first part will discuss the impact of the household use of modern cooking on energy expenditures and the second part will discuss the impact of the household's use of modern cooking fuels on health.

4.1.4.1 The Impact of household's use of modern cooking fuels on energy expenditures

The study found that a household's use of modern cooking fuel had a positive effect on its energy spending per month for both the country as whole (full sample) and in the urban areas (urban sample), (see table 10 in the appendix). We looked at this effect on four fronts, that is the effect on the household's (i) Total energy expenditure (ii) Modern energy expenditures (iii)

Modern energy budget share (iv) Charcoal expenditures (V) Traditional energy expenditure and (vi) Traditional energy budget share. Whereby the total energy expenditures constitute the household's expenditures on electricity, LPG, kerosene and charcoal per month, Modern energy expenditures constitutes of the household's expenditures on electricity and LPG per month. Moreover, charcoal expenditures constituted of a household's expenditures on charcoal per month while the traditional energy expenditures constituted the household's expenditures on charcoal and kerosene per month. The traditional and modern energy budget shares represent the share of the household's total energy expenditure allotted to traditional and modern energy fuels per month respectively.

A household's use of modern cooking fuels has a significant effect on a household's charcoal expenditures, modern fuel expenditures, traditional fuel expenditures and the proportions of energy expenditures on traditional and modern fuels (see table 10 in the appendix). Starting with the country level (full sample) analysis, using data from 3340 households after matching, of which 108 were treated and 3232 were controls, households that use modern cooking fuels (treated) were found to spend more on modern fuels and consequently allocate a higher proportion of their energy expenditures to modern fuels (LPG and electricity) compared to households that did not sue modern cooking fuels as their major cooking fuels (controls). On average the treated households spend 26,474 (USD 11.68[1]) Tanzanian shillings more per month on modern fuels than the control households. Furthermore, on average treated households spend 30 percentage points more of their energy budget on modern fuels per month than the control households. These differences in the amounts used on modern fuels by treated and control fuels households are significant at 1% level of significance (see table 10 in the appendix). On the other hand, treated households spend 14022 (USD 6.2) Tanzanian shillings less on charcoal per month compared to control households. This difference is significant at 1% level of significance. In an environment where multiple fuel use is highly dominant such savings are substantial to cover part of the modern cooking fuel budget. On average the treated and control households still spend 8523 and 22545 Tanzanian shillings on charcoal respectively. Based on the 2016 charcoal price depicted in Ishengoma and Abdallah (2016), the cost of 1 Kg bag of charcoal is around 500 to 1000 Tanzanian shillings. Thus the 14022 Tanzanian shillings savings are equivalent to around 14 kg to 28 kg reduction in charcoal consumption per month. Our findings are similar to Yonas et al, (2015) in Tanzania, where they found that LPG adoption reduced charcoal consumption and expenditures by 6 Kg and 3800 Tanzanian shillings per week. Furthermore, treated households spend less on traditional energy fuels (Charcoal and Kerosene) on a whole, whereby they spend 15,265 (USD 6.7) Tanzanian shillings less compared to control households (see table 11 in the appendix). Consequently, treated households spend a lesser share of their energy budget on traditional energy fuels. Whereby they spend thirty-three percentage points less of their energy budget on traditional energy fuels. The differences in expenditure and expenditure shares are significant at 1% level of significance. Nevertheless, the study did not find and significant difference in total energy expenditures between treated and control households.

The results for the urban sample are similar to what we had observed for the full sample. The urban areas analysis used 1081 households after matching, of which 1003 were controls and 78 were treated households. Households that use modern cooking fuels as their main cooking fuels were found to spend more on modern energy fuels in terms of actual expenditures and

[1] 1 USD= 2265.72 Tshs, as of 1st Oct 2018, source: Bank of Tanzania.

energy budget shares of such expenditures compared to control households. Whereby, not only do treated households spend 29028 (USD 12.8) Tanzanian shillings more on modern energy fuels per month but also, they spend 31 percentage points more of their energy budget on modern energy fuels compared to control households. These differences in expenditures and budget shares were significant at 1% level of significance. On the other hand, treated households in urban areas also spend less on charcoal, and on a whole traditional fuel. Households that use modern cooking fuels as their major fuels for cooking spend 16318 (USD 7.2) Tanzania shillings less on charcoal compared per month to control households. Based on the 2016 charcoal price depicted in Ishengoma and Abdallah (2016), the cost of 1 Kg bag of charcoal is around 500 to 1000 Tanzanian shillings. Thus the 16318 Tanzanian shillings savings are equivalent to around 16 kg to 33 kg reduction in charcoal consumption per month in urban areas. The study does not find any significant differences in total energy expenditures in urban areas between the treated and control households.

4.1.4.2 The Impact of household's use of modern cooking fuels on health

The study further looked at the impact of household use of modern cooking fuels on household's health and fertility using the 2015/16 Tanzanian Demographic and Health survey and Malaria indicator survey. The study specifically looked at the impact of household's use of modern cooking fuels on respiratory health of children aged five and below. The study investigated these impacts of household's use of modern cooking fuels on health for the full sample and the urban sample as was the case for the impact of household's use of modern cooking fuels on energy expenditures.

The impact on the children's respiratory health was explored by looking at the incidence of acute respiratory disease symptoms such as cough, fever and short breaths accompanied by chest problems. The study investigated the impact on the incidences of individual symptoms and combinations of symptoms among children aged five and below. The full sample analysis used data from 5555 households with at least one child aged five or below. Whereby 85 and 5470 households out of the 5555 households were treated and control households respectively. The study did not find any significant differences in the proportion of households with a child aged five years or below with at least one of the acute respiratory disease symptoms between the treated households and control households nor did we find any significant difference in the incidence of each individual symptom alone between the treated households and the control households (see Table 11 in the appendix). Nevertheless, the study found a significant difference in the proportion of households with children with all the self-reported respiratory symptoms between the treated households and control households, whereby a household's use of modern cooking fuels reduces the proportion of households with children with all the self-reported acute respiratory symptoms by 2.1 percentage points. Furthermore, the study found a significant difference between treatment and control groups in the proportion of households with children with cough and fever, whereby a household's use of modern cooking fuels reduced the proportion of households with children with fever and cough by 2.5 percentage points. The significant differences were significant at 5 percent level of significance (see Table 11 in the appendix). The fact that we could not isolate households that use modern cooking fuels only, those that use multiple cooking fuels and those using traditional cooking fuels only, nor measure the incidence with which the traditional fuels are used in multiple fuel use scenarios, may be the reasons attributed to the fact that there are no significant differences in the individual symptoms alone but rather a combination of such symptoms in children, probably an indication of the difference in the incidences of already manifested acute respiratory infections such as pneumonia, whose diagnosis may be attributed partly to a combination of symptoms such as a deep cough, fever, chest tightness and pleuritic chest pains (Short et al, 2017). Thus our results are similar to other studies in two ways, one it has ascertain the positive impact modern cooking stoves on health similar to studies that found a positive impact of improved/modern cooking fuels on health related outcomes (Bruwen and Levin, 2012; Smith et al, 2011; Lewis et al, 2017; Bensch and Peters, 2015) but secondly the fact that we could not find any significant effect for the individual symptoms independently reflects the importance of the intensiveness with which these modern cooking fuels are used in multiple fuels use scenario and the necessity of behavioural interventions when it comes to cooking so as to maximize the impacts of household's energy cooking transitions on health.

The results in the urban area are similar to what we saw for the whole sample. The urban analysis used data from 1518 households with at least one child aged five years of younger. Out of the 1518 households, 71 and 1447 were treated and control households respectively. Similarly, the study did not find any significant differences in the proportion of households with a child aged five years or below with at least one of the acute respiratory disease symptoms between the treated households and control households nor did we find any significant difference in the incidence of each individual symptom alone between the treated households and the control households (see Table 11 in the appendix). Nevertheless, the study found a significant difference in the proportion of households with children with all the self-reported respiratory symptoms between the treated households and control households, whereby a household's use of modern cooking fuels reduces the proportion of households with children with all the self-reported acute respiratory symptoms by 2.4 percentage points. Furthermore, the study found a significant difference between treatment and control groups in the proportion of households with children with cough and fever, whereby a household's use of modern cooking fuels reduced the proportion of households with children with fever and cough by 2.7 percentage points. The significant differences were significant at 5 percent level of significance (see Table 11 in the appendix).

4.1.5 Sensitivity Analysis

As the propensity score matching only controls for the observables, if there exist unobservable variables that affect assignment of households into treatment and the outcome variables simultaneously, a hidden bias may occur (Caliendo and Kopeining, 2008). Using the Rosenbaum (2002) bounding approach, the study checked the magnitude with which the selection process may be influenced by unobserved/unmeasured variables to alter the implications of the impact analysis. The study conducts a sensitivity analysis of all significant outcomes. The sensitivity analysis for the results of the impact of household use of modern cooking fuels on energy expenditures and child health shows that all our results are robust to any possible hidden selection bias (see table 10 and 11 in the appendix). The results indicate that the confidence intervals for the various significant effects would not include zero if unobserved variables caused the odds ratio of treatment assignment between the treatment and control households to differ by as much as 2.

4.2 The Impact of electrification on household welfare

4.2.1 Data description

The use of electricity in Tanzania as the main source for lighting has improved dramatically over recent years. Although the use of electricity for lighting is still very low in the rural areas, more than 50 percent of the urban population uses electricity as the main fuel for lighting. As seen in Table 12 in the appendix, for the country, 38.40 percent of households use electricity as their main fuel for lighting that is 1284 households out of the 3344 households. The use electricity for lighting is more prominent in urban areas, with about 64.35 percent of the households using electricity as their main fuel for lighting. The use of electricity in rural areas is still very low, with only 325 households (18.36%) out of the 1770 rural households sampled for the 2014/15 Tanzania national panel survey using electricity as main fuel for lighting. Based on the prominence of use of electricity, our analysis was restricted to the full sample (Country level), the urban sample and the rural sample.

The study used the 2014/15 wave of the Tanzanian national panel survey to investigate the impact of household's use of electricity on household's energy expenditures. The study used 3344, 1094 and 1770 households for the country (full sample), urban areas (urban sample) and the rural areas (rural sample) analyses respectively. Before matching, on the basis of the simple t-test, the treated and control households used for the full sample analysis were not statistically similar in any of the ten characteristics used as balancing covariates in the full sample analytical model (see table 13 in the appendix) while in the urban and rural sample the households were similar in only one of the characteristics used as balancing covariates in the urban and rural sample analytical models respectively (see table 14 and 15 in the appendix).

Similarly, the study used 2015/16 Tanzanian Demographic and health survey and malaria indicator survey to study the impact of household use of electricity on children's health and women's fertility. The study used 5557, 4170 and 1386 households for the country (full sample), rural areas (rural sample) and urban areas (urban sample) analyses respectively. Before matching, on the basis of the simple t-test, the treated and control households used in the full sample analysis were statistically similar in only two out of the seven characteristics used as balancing covariates in the full sample analytical model while households were similar in one and two characteristics for the urban and rural sample respectively used as balancing covariates in the urban sample analytical model (see table 16, 17 and 18 in the appendix). The statistical difference in the covariate means before matching in both data sets is largely expected (Caliendo and Kopeining, 2008), and thus comparing these group's outcomes of interest will result in biased results as these characteristics may simultaneously influence a household's treatment status and the outcomes of interest. To reduce such biases the study used propensity score matching to ascertain the best counterfactuals for our analyses.

4.2.2 Estimating the propensity scores

The study estimated the propensity scores for the individual samples in the respective data sets used. The study used the logit model to estimate the propensity scores. Table 19 and 20 in the appendix show the logit models used to estimate the propensity scores for households used for the impact of household use of electricity on expenditures, schooling, time use and health related outcomes respectively. The covariates used in the models were included based on the theory and literature of household cooking fuel choice. Moreover, as advised in Caliendo and Kopeining (2008), only those variables that simultaneously affect the treatment status of the households and the outcomes variables of interest were included in the models. Similarly, in this analysis, household income, education level of the household head, age of the household head, household's ownership of various assets like a house, mobile phones and televisions were among the variables that were included in the logit models used to estimate the propensity scores for the full sample, the rural sample and the urban samples of the respective data sets used for the analysis of the impact of household's use of electricity on household welfare indicators in Tanzania.

4.1.3 The common support and matching quality

The study then checked if the overlap condition was satisfied. Moreover, the matching quality was assessed for the sub samples, within the individual data sets that were used for the analysis of the impact of household use of electricity on non-health and health related outcomes respectively. The study thus assessed the common support and the matching quality for the fourth wave of the Tanzania national panel data set, used for the analysis of the impact of household use of electricity on energy expenditures, schooling and time use. As the analysis was done for the full sample, rural sample and the urban sample within the data set, we accordingly start with the full sample assessment. The easiest way to assess the common support is by looking at the distribution of propensity scores of the treatment and the control group. The distribution of the propensity scores and the common support region for the full sample analysis are presented in figure 5(see in the appendix). Out of the 3344 households used for the full sample analysis, 3258 were on the common support. The eighty-six households that were not on the common support were from the treatment group, which constituted of 1284 households. The kernel (Epanechnikov) matching with a bandwidth of 0.06, is the one that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores, whereby almost all the covariates after matching had standardized biases of 5 percent and below (See Table 13 in the appendix) and the mean standardized bias stood at 1.6 percent. Similarly, for the rural and urban sample, the common support and the distribution of the propensity scores are presented in figure 6 and 7 (see in the appendix). Out of the 1094 and 1770 households used for the urban and rural sample analysis respectively, 990 and 1767 were on the common support for the urban and rural sample respectively. The 104 and 3 households that were not on the common support for the urban and rural sample respectively, were from the treatment groups, which constituted of 704 and 325 households for the urban and rural sample respectively. The kernel (Epanechnikov) matching with a bandwidth of 0.06, is the one that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores for both the urban and the rural sample, whereby almost all the covariates after matching had standardized biases below 5% (See Table 14 and 15 in the appendix). The mean standardized biases stood at 2.8 and 2.3 percent for the urban and rural samples. Furthermore, the Pseudo-R2 after matching for all the sub samples (see Table 21 in the appendix) was considerably lower, meaning that there are no systematic differences in the distribution of the covariates between the treatment and the control groups of the respective samples. This is further ascertained by the joint significance test of the covariates after matching (see Table 21 in the appendix).

Secondly, the common support and the matching quality was assessed for the 2015/16 Tanzania demographic household survey, used for the analysis of the impact of household use of electricity on children's health and women's fertility. Similarly, the analysis was done for the full sample, rural sample and the urban sample within the data set. The study, starting with the full sample assessed the common support by looking at the distribution of propensity scores of the treatment and the control group. The distribution of the propensity scores and the common support region for the full sample analysis are presented in figure 8 (see in the appendix). All the 5556 households used for the full sample analysis were on the common support. Whereby 2236 were treated households and 3320 were control households. The kernel (Epanechnikov) matching with a bandwidth of 0.06, is the one that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores, whereby almost all the covariates after matching had standardized biases of 5% and below (See Table 16 in the appendix) and the mean standardized bias stood at 2.1 percent. Similarly, for the rural and urban samples, the common support and the distribution of the propensity scores are presented in figure 9 and 10 (see in the appendix). Out of the 1386 and 4170 households used for the urban and rural sample analysis respectively, 1351 and 4168 were on the common support for the urban and rural sample respectively. The 35 and 2 households that were not on the common support for the urban and rural sample respectively, were from the treatment groups, which constituted of 912 and 1324 households for the urban and rural sample respectively. The kernel (Epanechnikov) matching with a bandwidth of 0.06 and 0.02 were the ones that gave the best matching quality in terms of the mean of the standardized biases and the standardized biases of the individual covariates used in the estimation of the propensity scores for the urban and rural samples respectively. Whereby almost all the covariates after matching had standardized biases below 5% (See Table 17 and 18 in the appendix) and the mean standardized stood at 2.8 and 2.3 for the rural and urban sample respectively. Furthermore, the Pseudo-R2 after matching for all the sub samples (see Table 21 in the appendix) was considerably lower, meaning that there are no systematic differences in the distribution of the covariates between the treatment and the control groups of the respective samples. This is further ascertained by the joint significance test of the covariates after matching (see Table 21 in the appendix).

4.2.4 The Treatment effect

This section presents the discussion on the effect of household's use of electricity on the household's welfare. The section is divided into sub sections to discuss the impact of the household's use of electricity on energy expenditures, schooling, time use, health and fertility for the full samples and the other sub samples in the study.

4.2.4.1 The impact of household electrification on energy expenditures

The use of electricity was found to have a significant effect on the household energy expenditures (see Table 22 in the appendix). Starting with the full sample analysis, the study finds a significant impact of household use of electricity on the household's total energy expenditures. Whereby treated households spend 9894 (USD 4.36) Tanzanian shillings more on household energy expenditures per month compared to control households. This difference in total energy expenditures was significant at one percent level of significance. The study's findings are similar to what other impact studies had ascertained, that household use of electricity, particularly on-grid connection leads to an increase in total expenditures and a rise in energy expenditures (Bonan et al., 2016; Bensch et al., 2011; van de Walle et al., 2015). Although other studies point that the use of electricity from other sources, such as solar PV may lead to lower energy expenditures (Arraiza and Calero, 2014; Samad et al, 2013), our study's results are driven by the fact that grid-connections accounts for 75 percent of household's source of lighting fuel in Tanzania. Studies have shown that acquiring of new electrical appliances and intensive use of lighting overcompensates the efficiency gains from household's switch from traditional sources of lighting to electricity. In coherence to this finding, treated households were found to spend more on modern fuels in terms of expenditures and budget shares (see table 22 in the appendix). Whereby treated households spend 12558 (USD 5.54) Tanzanian shillings and 32.5 percentage point more per month on modern fuel expenditures and budget shares respectively. This difference was significant at 1 percent level of significance.

On the other hand, household's use of electricity was found to decrease household kerosene expenditures. This is in accordance to out theory change, attributed to the fact that electricity replaces kerosene, which is used as the main lighting fuel for 27 percent Tanzanian households. On average, treated households were found to spend 2584 (USD 1.14) Tanzanian shilling less on kerosene per month compared to control households (see table 22 in the appendix). The difference in kerosene expenditures between the treated and control groups is significant at one percent level of significance. Our findings are similar to what Karumba and Muchapondwa (2017) and Grimm et al, (2015) found for the case of Kenya and Rwanda respectively. The continued use of kerosene by treated households maybe for lighting in times of power outages and for cooking, as our sample shows that 2.8 percent of the households use kerosene for cooking. In coherence to these findings treated households were found to spend less on traditional energy fuels both in terms of expenditures and budget shares (see table 22 in the appendix). Whereby treated households spend 2664 (USD 1.18) Tanzanian shillings and 34 percentage point less per month on traditional fuel expenditures and budget shares respectively. This difference was significant at 1 percent level of significance.

Furthermore, the study investigated if the impacts on the various energy expenditures were any different in the rural and urban sub-samples. The study found that all but one of the results remained the same in terms of signs and significance for both rural and urban sample. Whereby there were significant differences in modern energy expenditures, modern energy budget shares, traditional energy expenditures, traditional energy budget shares and kerosene expenditures between the treated and control households in both the urban and rural samples (see table 22 in the appendix). Nevertheless, whereas the study found significant increases in total energy expenditures for the urban sample as it was for the full sample analysis due to household's use of electricity, corresponding increases in the rural sample were not statistically significant. It's highly probable that this is because of the households in the rural areas derive their electricity from solar, as it accounts for 73 percent of the household's source of electricity for lighting compared to 27 percent of households connected to the grid in rural areas among the electrified households. Thus, limiting the use of electricity for most rural households.

4.2.4.2 The impact of household electrification on schooling

The study further found evidence of the impact of household's use of electricity on schooling. The study looked at various schooling indicators namely study hours, education years and passing of national standard seven exams (see table 23 in the appendix). The analysis was done for households that had children in the Tanzanian school going age that is between 5 and 20 years of age. The analysis used 1814 for the full sample analysis, that had at least a child aged 5 and 20 attending school. On the other hand, the study used 1263 and 1262 households that had at least one male child and one female child respectively to study the impact of household use of electricity on schooling outcomes for boys and girls respectively. The study found significant differences in the study hours between the treated and control group (see table 23 in the appendix). Children in treated households study an hour more per week than children in control households. Furthermore, the study finds significant differences in study hours among male and female children in the full samples. Whereby both male and female children in treated households study an hour more per week compared to their counterparts in the control households. Our findings are similar to what other studies found and substantiated in Bangladesh and Peru (Samad et al., 2013; Arraiz and Calero, 2015).

The study further investigated if a household use of electricity influenced the years of schooling of children aged between 5 and 20, attending school. The study finds a significant difference in the years of schooling between children in treated and control households (see table 23 in the appendix). The difference was significant at five percent level of significance. Furthermore, the study found significant differences in schooling years between female children in the treated and control group but did not find any significant differences years of schooling for male children in control and treated households (see table 23 in the appendix). The significant difference in years of schooling are a suggestive evidence more study hours for children in electrified household's manifests in better schooling outcomes and thus children moving further in terms of education attainment. Similarly, Arraiz and calero (2015) and Khandker et al., (2013) found significant effects on schooling in Peru and Vietnam respectively. Nevertheless, the study did not find any significant difference is the proportion of households, with at least one child that sat for and passed the standard seven examinations. The study only found significant differences for boys but not girls (see table 23 in the appendix).

On the other hand, the study found that the impact of household's use of electricity manifests itself differently in different contexts as portrayed by our results for the rural and urban sub samples. The study finds significant differences in study hours between children in treated and control for both the rural and urban samples (see table 23 in the appendix). Nevertheless, the study does not find any significant differences in study hours among male children nor female children in the treated and control households in the rural sample. On the other hand, these differences were significant for the urban sample. Whereby, a household's use of electricity is associated with an increase of study hours by approximately 2 and 3 hours a week for male and female children respectively. These differences were to be significant at 5 percent level of significance.

Furthermore, whereas there are no any significant differences in years of schooling between children in the treated and control households in the urban sample, these differences are significant for the rural sample. This suggests that there may be spill over effects in the urban areas, for the two groups to have years of schooling that are statistically similar. Nevertheless, the study finds significant differences in years of schooling between female children in the treated and control households in the urban sample but not for the rural sample. This may be because electricity makes a day for the girl child longer, thus be able to study longer in the evenings after their chores and this manifests in more years of schooling. This may not manifest in the rural areas due to different priorities for the girl child in the villages. On the other hand, the study does not find any significant differences in years of schooling between male children in treated and control households. The study does not find any significant effect of a household's use of electricity on the overall children's passing of standard seven examinations for the rural and urban samples. Nevertheless, the study finds significant differences for female children in the rural sample.

4.2.4.3 The impact of household electrification on time use

The study also looked for evidence of time use changes by households due to use of electricity by households. Starting with the full sample, the study did not find any significant differences in the proportion of households whose household members that spent most of their time in non-agricultural activities (see Table 24 in the appendix) between the treated and control households. Furthermore, the study did not find any significant differences in the proportion of households whose male household members spent most of their time in non-agricultural activities nor in the proportion of households whose female household members spent most of their time in non-agricultural activities between the treated and control households. Similarly, we did not find any significant differences in the urban sample.

Although we did not find any significant differences in the proportion of households whose male household members spent most of their time in non-agricultural activities nor the proportions of households whose female household members spent most of their time in non-agricultural activities between treated and control households in the rural sample, we found a significant difference in the proportion of households whose household members spent most of their time in non-agricultural activities. Household's use of electricity increases the proportion of households whose members spend most of their time in non-agricultural activities by 7 percentage points. Our results are consistent with the theory of change that stipulates that such shifts by household members from agricultural to non-agricultural activities which electricity contributes in their development to be more significant in rural areas, as in the urban areas due to spill over effects and the vastness of informal sector, members in the control group are also mostly employed in the non-agricultural sector. This study's findings are similar to what Aevarsdottir et al., (2017) also found in rural Tanzania. Their study substantiated that household use of electricity in rural areas increased labour supply on a whole by 8 percentage points. Our results support findings in other studies that find a significant impact on time use and labour supply. (Arraiz and Calero, 2015; Samad et al, 2013; Khandker et al, 2012; Bensch et al, 2011; Bernard and Torero, 2015; Barron and Torero, 2015; Aguirre, 2014). Nevertheless, these impacts differ in different contexts, whereas some studies find an overall significant impact on time spent in non-agricultural activities (Aevarsdottir et al., 2017) others find these effects being significant for either male or females (Arraiz and Calero, 2015; van de Walle et al., 2015).

4.2.4.4 The impact on health and fertility

The study further looked at the impact of household use of electricity on the respiratory health of children aged five and below and on the women's fertility. Starting with the children's respiratory health, the study investigated if a household's use of electricity had an impact on the incidences of various individual symptoms of respiratory infections that is cough, fever and short breaths accompanied by chest problems and various combinations of such symptoms on children aged five and below.

Starting with the full sample analysis, the study did not find any significant effect of household's use of electricity on respiratory infections symptoms for children aged five and below (see table 25 in the appendix). The study did not find any significant differences between the incidences of the individual symptoms nor various combinations of the symptoms between the treated households and the control households. Our results are contrary to what a few studies that have looked at the impact of electrification on respiratory infections substantiated. Whereas, Barron and Torero (2017) found significant improvement of air quality and a reduction of acute respiratory infections among children aged six and below in El Salvador, the contexts of the study differ in the sense that, for a country like Tanzania where household's use of biomass fuel is over 90 percent (National Bureau of Statistics, 2015a) and over 30 percent of households still cook in the house, the pay-offs of electrification with regards to health may be hard to substantiate for children aged five years and below. Although Aevarsdottir et al., (2017) substantiates such effects on health in Tanzania for all household members, their results are only significant when heterogeneity of treatments are considered. The results for the rural and urban sample analysis also show no significant differences in the incidences of respiratory symptoms on children aged five and below between the treated and control households.

The study further looked into the impact of electrification on fertility (see Table 26 in the appendix). The study used the number of children aged five and below, the number of births in the last five years, the preferred waiting time before the next pregnancy and the use of contraceptives as indicators of fertility in the households. The analysis was similarly done for the full sample and the two sub-samples that is rural and urban samples.

The full sample analysis results show no significant results between the treated and control households, in the number of children aged five and below in the households, number of births in the last five years and the preferred waiting time before the next pregnancy by women in the households. Nevertheless, the full sample analysis shows a significant difference in the proportion of households with women that use contraceptives for birth control. Whereby, a household's use of electricity increases the proportions of households with a woman that uses contraceptives by 4.4 percentage points (see table 26 in the appendix). A household's use of electricity may induce such impacts through improved access and use of information technologies (Arraiz and Calero, 2015). According to the Tanzania Demographic health survey 2015/2016, the use of contraceptives has increased from 27 percent to 32 percent. One of the challenges organizations have always faced in promoting family planning is getting these services and education about family planning to the majority of the population, especially in the remoteness of rural areas (USAID, 2017). Nevertheless, among the interventions used to raise awareness and use of family planning services, is the use of national mass media campaigns (USAID, 2017). Nevertheless, although such information may be helpful in increasing the awareness and use of family planning, it can only work if such information goes hand in hand with up scaling of family planning services, training of service providers and other modes of service delivery for the impacts to be realized. The study also finds a significant effect of household's use of electricity on the contraceptive use, but the effect was not significant in the rural areas. The study only finds a significant difference in the preferred waiting time before the next pregnancy. Whereby, a household's use of electricity to an increase in the proportion of households with women who prefer to wait at least two years before their next pregnancy by 3 percentage points. This is may be because, information dissemination on family planning through media and other information technologies might have reached the rural areas, but as modern family planning services centres have not been established in remote areas of yet, women are already sensitized to actually make decisions with regards to the time between pregnancies.

4.2.5 Sensitivity analysis

As the propensity score matching only controls for the observables, if there exist unobservable variables that affect assignment of households into treatment and the outcome variables simultaneously, a hidden bias may occur (Caliendo and Kopeining, 2008). Using the Rosenbaum (2002) bounding approach to check the magnitude with which the selection process may be influenced by unobserved/unmeasured variables to alter the implications of the impact analysis. Similarly, the study conducted a sensitivity analysis of all significant outcomes due to a household's use of electricity as done in the previous section for impacts of household's use of modern cooking fuels. The sensitivity analysis for the results of the impact of household use of electricity on energy expenditures results show that most of our results are robust to any possible hidden selection bias (see table 22 in the appendix). The results indicate that the confidence intervals for the various significant effects would not include zero if unobserved variables caused the odds ratio of treatment assignment between the treatment and control households to differ by 2.

Nevertheless, our results on the impact of household's use of electricity on traditional energy expenditures for the full sample and urban sample, modern energy budget and modern energy expenditures share for the rural sample are sensitive to possible deviations from unconfoundedness assumptions due to unobservable factors. The lowest critical values at which these results are sensitive to possible deviation is 1-1.1 for modern energy expenditures and modern energy budget shares outcomes, while the largest critical values are for traditional energy expenditures for the full sample 1.5-1.6. Our results on schooling for all the sub samples are also sensitive to possible deviations from unconfoundedness assumptions (see table 23 in the appendix). The lowest critical value at which our results are sensitive is 1-1.1 and the highest being 1.8-1.9. Furthermore, our results on time use are also sensitive at a critical value of 1.2-1.3 (see table 24 in the appendix). Nevertheless, our results on fertility, are robust to any possible deviations from unconfoundedness assumptions, except for outcomes in the rural and urban samples that were sensitive at critical values of 1.4-1.5 (see table 26 in the appendix).

It is of note that, a sensitivity analysis assesses the strength unmeasured confounders would require changing inferences about the treatment effects, thus the critical values are gradually increased to a point which inference about the treatment effect might change. Thus, these are worst case scenarios and do not imply unobserved heterogeneity (Caliendo et al., 2005). These results only state that the confidence intervals for the various significant effects that are sensitive to possible deviations from unconfoundedness assumptions, may include zero if unobserved variables caused the odds ratio of treatment assignment between the treatment and control households to differ by a certain critical value. Additionally, our results are relatively robust, as most of them are not sensitive to possible deviation from unconfoundedness assumptions. Those that are sensitive, require a big differential in odds for inferences about treatment effects to change. Nevertheless, those that are sensitive at low critical levels of 1-1.1 doesn't mean they are not robust enough, but rather should be interpreted within those restrictions (Caliendo et al., 2005).

5. Conclusion

The main objective of the study was to look at the impacts of household energy transition on the household welfare indicators in Tanzania. The study looked at the impact of household's use of modern cooking fuels on household welfare and the impact of household use of electricity on the household welfare. Using two nationally representative data sets, that is the fourth wave of the Tanzanian National Panel Survey 2014/2015 and the Tanzanian Demographic and Health Survey and Malaria indicator survey 2015/2016 to ascertain the impact of household energy transition on the household welfare in Tanzania. The study employed propensity score techniques to come up with suitable counterfactuals for treated households based on observable characteristics. Propensity scores were estimated using logit models that constituted covariates that simultaneously affect the treatment status and outcomes of interest. The treated and control households were matched based on the estimated propensity scores. The matching quality was assessed, and all the tests showed that the matching was successful. A sensitivity analysis conducted showed that our results are relatively robust to possible deviations from unconfoundedness assumptions.

The study finds significant impacts of household's use of cooking fuels on charcoal consumption, which translates into a decrease of charcoal consumed. The promotion of use of modern cooking fuels may help cut down on the amount of charcoal consumed, especially in the urban areas. With the rolling of the natural gas for home consumption in the pipeline as test phase, households should be made more aware of such ventures, so to help cut back on charcoal consumption. Furthermore, the study found suggestive evidence for impacts of household's use of modern cooking fuels, policies advocating a reduction in excessive use of charcoal and other traditional cooking by shifting to sue of modern cooking fuels may go a long way in reducing hospital visits by children attributed to respiratory infections.

Household's use of electricity was found to improve schooling outcomes, the increase in study hours which manifests in an increase of years of schooling is an important and significant outcome from the study. Although schooling outcomes may not be attributed to electricity alone, but our study give suggestive evidence that electricity may be important in augmenting other factors in improving schooling outcomes. Moreover, our study provides the first evidence in Tanzania, that electricity may help smoothen information flow in rural and urban areas and augment various social campaigns like family planning as portrayed in this study. Furthermore, the benefits that electrification may bring in rural areas by supporting small businesses and elongating a working day, may go a long way improving a household's welfare. Thus, the government should enhance electrification programmes to enable communities to extract such pay offs.

Further research to elicit differential in impacts of household's use of modern cooking fuels, for households that use modern cooking fuels alone and those that use multiple fuels. A multiple treatment type of study that looks at where the food is cooked by a household and the type of fuel used may elicit more precise impacts of modern cooking fuels on the household welfare. On the other hand, further research to differentiate the benefits of electrification from various sources of electricity, in this case grid-electricity and renewable sources of electricity like solar power that may be limited only for lighting may of interest.

Works Cited

Abadie, A. & Imbens, G., 2008. On the Failure of the Botstrap for Matching Estimators. *Econometrica*, 76(6), pp. 1537-57.

Adrianzén, M. A., 2013. Improved cooking stoves and firewood consumption: Quasi-experimental evidence from the Northern Peruvian Andes. *Ecological Economics,* pp. 135-143.

Aevarsdottir, M. A., Barton, N. & Bold, T., 2017. *The impacts of rural electrification on labor supply, Income and and health E-89302-TZA-1,* London: International Growth Centre.

Aguirre, J., 2017. Impact of rural electrification on education: A case study from Peru. *The Lahore Journal of Economics,* p. 91–108.

Alem, Y., Hassen, S. & Köhlin, G., 2014. Adoption and Disadoption of electric cookstoves in urban Ethiopia. *Resource and energy economics,* pp. 110-124.

Alem, Y., Hasssen, S. & Kohlin, G., 2014. adoption and disadoption of electric stoves in urban Ethiopia: Evidence from panel data. *Resource and Energy economics,* pp. 110-124.

Alem, Y., Ruhinduka, R., Berck, P. & Bluffstone, R., 2015. *Credit, LPG stove adoption and Charcoal consumption:Evidence from randomized control trial; E-89225_TZA-1*, London: International Growth Centre.

Aliston, J. M., Foster, K. A. & Gree, R. D., 1994. Estimating Elasticities with the Linear Approximate Almost Idal demand System: Some Monte carlo results. *The Review of Economics and Statistics,* pp. 351-356.

Andadari, R. K., Mulder, P. & Rietveld, P., 2014. Energy poverty reduction by fuel switching. Impact evaluation of the LPG conversion program in Indonesia. *Energy Policy, 66* , pp. 436-449. doi:10.1016/j.enpol.2013.11.021.

Arraiz, I. & Calero, C., 2015. From Candles to Light: The Impact of Rural Electrification. *IDB WORKING PAPER SERIES No. IDB-WP-599,* pp. May, 2015.

Azimoh, C. L., Klintenberg, P., Wallin, F. & Karlsson, B., 2015 . Illuminated but not electrified: An assessment of the impact of Solar Home System on rural households in South Africa. *Applied Energy, 155* , pp. 354-364. doi:10.1016/j.apenergy.2015.05.120.

Baker, P., Blundell, R. & Mickelewright, J., 1989. Modelling Husehold energy expenditures using micro-data.. *Economic Journal 99,* pp. 720-738.

Barron, M. & Torero, M., 2015. *Electrification and Time Allocation,* s.l.: MPRA Paper No. 63782.

Barron, M. & Torero, M., 2017. Household electrification and indoor air pollution. *Journal of Environmental Economics and Management,* Volume 86, pp. 81-92.

Beltramo, T. & Levine, D. I., 2013. The effect of solar ovens on fuel use, emissions and health: results from a randomised controlled trial. *Journal of Development Effectiveness,* pp. 178-207.

Bensch, G., Grimm, M. & Peters, J., 2015 . Why do households forego high returns from technology adoption? Evidence from improved cooking stoves in Burkina Faso. *Journal of Economic Behavior and Organization, 116* , pp. 187-205. doi:10.1016/j.jebo.2015.04.023.

Bensch, G., Kluve, J. & Peters, J., 2011. Impacts of Rural Electrification in Rwanda. *IZA Discussion Paper No. 6195.*

Bernard, T. & Torero, M., 2014. Social Interactions Effects and Connection to Electricity: Experimental Evidence from Rural Ethiopia. *Munich Personal RePEc Archive,* pp. MRA paper No 61303, online at http://mpra.ub.uni-muenchen.de/61303/.

Bernard, T. & Torero, M., 2015. Social interaction effects and Connection to Electricity: Experimental evidence from rural Ethiopia. *MPRA paper No. 61303,* pp. http://mpra.ub.uni-muenchen.de/61303/.

Blundell, R., 1988. Consumer Behaviour: theory and emperical evidence- a survey. *Economic Journal 98 (389),* pp. 16-65.

Bollinger, B. & Gillingham, K., 2010. Environmental Preferences and Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Market science working paper.*

Bonan, J., Pareglio, S. & Tavoni, M., 2014. Access to Modern energy: A review of impact evaluations. *Fondazione Eni Enrico Mattei.*

Brooks, N., 2014. Do Clean Cookstoves Reduce Biomass Fuel Consumption?. *(unpublished Masters thesis),* pp. The Sanford school of public policy, Duke University.

Brooks, N. et al., 2016. How much do alternative cookstoves reduce biomass fuel use? Evidence from North India. *Resource and Energy Economics,* p. 153–171.

Bruce, N., Pope, D., Rehfuess, E. & Balakrishnan, K., 2015. Strategy implications of new evidence on interventions and exposure risk functions. *Atmospheric Environment,* pp. 451-457.

Burwen, J. & Levine, D. I., 2012 . A rapid assessment randomized-controlled trial of improved cookstoves in rural Ghana. *Energy for Sustainable Development,* p. 328–338.

Bwenge, S. N., 2011. *The Effects of Adopting Improved Wood Stoves on the Welfare of Rural Women: A case of Kibaha District in Tanzania,* Netherlands: Van Hall Larenstein University of Applied Sciences.

Caliendo, M., Hujer, R. & Thomsen, S. L., 2005. The Employment effects of Job Creation Schemes in Germany: A Microecometric Evaluation. *IZA Discussion Paper No. 1512.*

Caliendo, M. & Kopeinig, S., 2008. Some practical guidance for the implemntation of propensity score matching. *Journal of economic surveys,* 22(1), pp. 31-72.

Chambwera, M. & Folmer, H., 2006. Fuel switching in Harare: An almost ideal demand system. *Energy Policy,* pp. 2538-2548.

Chen, Q., Yang, H., Liu, T. & Zhang, L., 2016 . Household biomass energy choice and its policy implications on improving rural livelihoods in Sichuan, China. *Energy Policy, 93* , pp. 291-302. doi:10.1016/j.enpol.2016.03.016.

D'Agostino, A. L., Urpelainen, J. & Xu, A., 2015. Social-economic determinants of charcoal expenditures in Tanzania. *Energy Economics,* pp. 472-481.

Dasso, R. & Fernandez, F., 2015. The effects of electrification on employment in Peru. *IZA Journal of Labour and Development,* 6(4).

Deaton, A. & Muellbauer, J., 1980a. An almost Ideal Deamnd System. *The American economic Review,* pp. 312-326.

DIE, 2016. *German developemnt institte.* [Online]
Available at: https://www.die-gdi.de/uploads/media/BP_14.2016.pdf

Dresen, E. et al., 2014. Fuelwood Savings and Carbon Emission Reductions by the Use of Improved Cooking Stoves in an Afromontane Forest, Ethiopia. *Land 3,* pp. 1137-1157; doi:10.3390/land3031137.

EDWARDS, J. H. Y. & LANGPAP, C., 2012. Fuel choice, indoor air pollution and children's health. *Environment and Development Economics 17,* p. 379–406.

Energy and Water Utilities Regualtoru Authority [Tanzania], 2016. *Downstream Petroleum Sub Sector Performance Review Report,* Dar es salaam: United Republic of Tanzania.

EngenderHealth, 2016. *Increasing family planning capacity, access, and quality: Results from EngenderHealth's ExpandFP Project in Tanzania. Results Brief.,* New York: s.n.

Ezzati, M. & M, K. D., 2001. Indoor air pollution from biomass combustion and acute respiratory infections in Kenya: an exposure response study. *The Lancet*, Issue 358, pp. 619-624.

Flores-Lagunes, A., Gonzalez, A. & Neumann, T. C., 2007. Estimating the Effects of Length of Exposure to a Training Program: The Case of Job Corps. *Institute for the study of labor (IZA),* pp. Discussion Paper No. 2846, June 2007.

Foel, W., Pachauri, S., Spreng, D. & Zerriffi, H., 2011. Household cooking fuels and technologies in developing economies. *Energy Policy,* p. 7487–7496.

Furukawa, C., 2014. Do Solar Lamps Help Children Study? Contrary Evidence from a Pilot Study in Uganda. *Journal of Development Studies,* 50(2), pp. 319-341.

Graziano, M. & Gillingham, K., 2015. Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment. *Journal of Economic Geography,* pp. Vol.15, pp. 185-839.

Grimm, M., Munyehirwe, A., Peters, J. & Sievert, M., 2016. A First Step Up the Energy Ladder? Low Cost Solar Kits and Household's Welfare in Rural Rwanda-WPS7859. *Policy Research Working Paper 7859.*

Guta, D. D., 2012. Application of an almost ideal demand system (AIDS) to Ethiopian rural residential energy use: Panel data evidence. *Energy Policy,* pp. 528-539.

Hanna, R., Duflo, E. & Greenstone, M., 2016. Up in Smoke: The Influence of Household Behavior on the Long-Run Impact of Improved Cooking Stoves. *American Economic Journal: Economic Policy,* p. 80–114.

Hazra, S., Lewis, J., Das, I. & Kumar, S. A., 2014. Adoption and Use of Improved Stoves and Biogas Plants in Rural India. *SANDEE Working Papers No. 86–14,* pp. ISSN 1893-1891.

Heltberg, R., 2004. Fuel switching: evidence from eight developing countries. *Energy Economics,* pp. 869-887.

Hirano, K. & Imbens, G., 2004. The propensity score with continuous treatments. *Applied Bayesian modelling and causal inference from incomplete data perspectives* , pp. 73-84.

Hnyine, Z. T., Lubis, W., Sagala, S. & Yamin, D., 2015. Analysing the economic benefits of rural biogas adoption in Selo Sub-District, Boyolali, Indonesia. *Working paper series No. 8, August 2015.,* p. Resilience development initiative.

Holmes, S. M., 2010. *Potential Effects of Improved Cookstove Use and Barriers to Acceptance: A Case Study Measkron, Tanzania,* Olympia: The Evergreen State College .

IEA, 2010. *World energy outlook 2010,* Paris: International energy Agency.

IEG (Independent Evaluation Group), 2008. *The Welfare Impact of Rural Electrification: A reassessement of costs and benefits*, Washington: World Bank.

Imbens, G., 2000. Teh role of the propensity score in estimating dose-response functions. *Biometrika 87(3),* pp. 706-710.

Ishengoma, R. & Abdallah, J., 2016. *Charcoal market conditions in 2016 in Dar es Salaam and Morogoro, Tanzania*, Dar-es-salaam: Swiss agency for Development and Cooperation (SDC).

Jain, J. K., 2014. Impact of Adoption of Biogas Plant on Socio-Economic Status of the Biogas Users in Ujjain District of Madhya Pradesh. *(unpublished masters thesis),* pp. Rajmata Vijayaraje Scindia Krishi Vishwa Vidyalaya, Gwalior College of Agriculture.

Jeuland, M. et al., 2014. Preferences for Improved Cook Stoves: Evidence from North Indian Villages. *DUKE ENVIRONMENTAL AND ENERGY ECONOMICS WORKING PAPER SERIES,* pp. Working Paper EE 14-07, July 2014.

Karimu, A., 2015 . Cooking fuel preferences among Ghanaian Households: An empirical analysis. *Energy for Sustainable Development, 27 ,* pp. 10-17. doi:10.1016/j.esd.2015.04.003.

Karimu, A., Mensah, J. T. & Adu, G., 2016 . Who Adopts LPG as the Main Cooking Fuel and Why? Empirical Evidence on Ghana Based on National Survey. *World Development, 85* , pp. 43-57. doi:10.1016/j.worlddev.2016.05.004.

Karumba, M. & Muchapondwa, E., 2017. The impact of micro hydroelectricity on household welfare indicators. *ERSA working paper 659.*

Khandker, S. R., Barnes, D. F., Samad, H. & H, M. N., 2008. Welfare Impacts of rural Electrification: Evidence from Vietnam. *World bank.*

Khandker, S. R., Samad, H. A., Ali, R. & Barnes, D. F., 2012. Who Benefits Most from Rural Electrification?: Evidence from India. *World Bank, Policy Research Working Paper 6095.*

Kibrom, A. A., Goytom, K. A. & Guush, B., 2017. Social Networks and Factor Markets: Panel Data Evidence from Ethiopia. *The Journal of Development Studies,* p. DOI:10.1080/00220388.2017.1288224.

Kimemia, D. & Annegarn, H., 2016. Domestic LPG interventions in SouthAfrica: Challenges and lessons. *Energy Policy 93,* pp. 150-156.

La Ferrara, E., Chong, A. & Duryea, S., 2008. *Soap Operas and Fertility: Evidence from Brazil,* Washington, DC: Inter-American Development Bank.

Lewis, J. J., 2015. Measuring Impacts of Improved Cookstove Interventions on Technology Adoption and Environmental and Health Outcomes. *(Doctoral Dissertation),* p. Retrieved from Duke University library database (Publication NO.3739946).

Lewis, J. J. et al., 2017. Biogas Stoves Reduce Firewood Use, Household Air Pollution, and Hospital Visits in Odisha, India. *Environmental science and technology,* p. 560−569.

Liu, J. & Florax, R. J., 2014. *The effectiveness of International aid: A Generalized Score analysis.* Minneapolis, July 27-29, 2014.

Manski, C., 1993. Identification of endogeneous: The reflection problem. *Review of Economic studies 60 (3).*

Masatsugu, L. & Pattanayak, S. K., 2017. *Household cooking technologies and REDD+:Pilot experiences in Tanzania and across the tropics,* Duke: Duke University.

Massawe, F. A., Bengesi, K. M. K. & Kweka, A. E., 2015. Patterns of Household Cooking Energy and Associated Factors: Experience from Kilimanjaro Region, Tanzania. *Intersect, Vol 8, No 3* .

Mensah, J. T. & Adu, G., 2015 . An empirical analysis of household energy choice in Ghana. *Renewable and Sustainable Energy Reviews, 51* , pp. 1402-1411. doi:10.1016/j.rser.2015.07.050.

Mercado, I. R. & Masera, O., 2015. Patterns of stove use in the context of Fule device stacking: Rationale and implications. *Eco Health,* pp. 42-56 DOI: 10, 1007/s10393-015-1009-4.

Miller, G. & Mobarak, A. M., 2014. Learning About New Technologies Through Social Networks: Experimental Evidence on Nontraditional Stoves in Bangladesh. *Marketing Science, Articles in Advance,* p. 1–20.

Mukong, A. K. & Burns, J., 2015. Social networks and Maternal health utilization in Tanzania. *ERSA working paper 540,* p. August 2015.

Mwampamba, T., 2007. Has the wood fule crisis returned? Urban Charcoal consumption in Tanzania and its implications to present and future forest availability. *Energy policy,* pp. 4221-4234.

Nansaior, A., Patanothai, A., Rambo, T. A. & Simaraks, S., 2011. Climbing the energy ladder or diversifying energy sources? The continuing importance of household use of biomass energy in urbanizing communities in Northeast Thailand. *b i o m a s s and b i o energy,* pp. 4180-4188.

National Bureau of Statistics [Tanzania], 2016. *Tanzania Demographic and helath survey and Malaria Inidcator Survey,* Dar-es-salaam, Tanzania and Rockville Maryland, USA: MoHCDGEC, MoH, NBS, OCGS and ICF.

National Bureau of Statistics [Tanzania], 2016. *Tanzania National Panel Survey Report (NPS)-Wave 4,* Dar-es-salaam, Tanzania: NBS.

National Bureau of statistics, 2013. *Key findings 2011/12 Household budget survey Tanzania Mainland,* Dar-es-salaam: National Bureau of Statistics and the Ministry of finance and planning.

National Bureau of Statistics, 2015. *2012 Population and Housing census: Housing condition, household amenities and assets monograph,* Dar-es-salaam: National Bureau of statistics and Ministry of finance and planning.

National bureau of Statistics, 2015a. *Environmental statistics 2014: Tanzania mainland,* Dar-es-salaam: Ministry of finance.

National Bureau of Statistics, 2015b. *2012 Population and Housing census: Housing condition, household amenities and assets monograph,* Dar-es-salaam: National Bureau of statistics and Ministry of finance and planning.

Ngui, D., Mutua, J., Osiolo, H. & Aligula, E., 2011. Household energy demand in Kenya: An application of the linear approximate almost ideal demand system (LA-AIDS). *Energy policy,* pp. 7084-7094.

Ortiz-Correa, J. S., Filho, M. R. & Dinar, A., 2016. Impact of access to water and sanitation services on educational attainment. *Water Resources and Economics 14,* pp. 31-43.

Peters, J. & Sieverta, M., 2016. Impacts of rural electrification revisited – the African context. *JOURNAL OF DEVELOPMENT EFFECTIVENESS, VOL. 8, NO. 3,* p. 327–345.

Peters, J. & Vance, C., 2011. Rural electrification and Fertility: Evidence form Cote d'Ivore. *Journal of Development studies,* 12(2), pp. 111-134.

Putra, R. A. R. S., Liu, Z. & Lund, M., 2017. The impact of biogas technology adoption for farm households – Empirical evidence from mixed crop and livestock farming systems in Indonesia. *Renewable and Sustainable Energy Reviews 74* , p. 1371–1378.

Quansah, R. et al., 2017. Effectiveness of interventions to reduce household air pollution and/or improve health in homes using solid fuel in low-and-middle income countries: A systematic review and meta-analysis. *Environment International,* pp. 73-90.

Rahut, D. B., Behera, B. & Ali, A., 2015 . Household energy choice and consumption intensity_ Empirical evidence from Bhutan. *Renewable and Sustainable Energy Reviews, 53* , pp. 993-1009. doi:10.1016/j.rser.2015.09.019.

Rosenbaum, P. R., 2002. *Observational Studies.* Newyork: Springer.

Rosenbaum, P. & Rubin, D., 1985. Constructing a control group using multivariate matched sampling methods that incoporate the Propensity Score. *The American Statistician,* Volume 39, pp. 33-38.

Rosenbum, P. R. & Rubin, D. B., 1983. Teh central role of the propensity score in observational studies for causal effects.. *Biometrika 70(1),* pp. 41-55.

Roy, A., 1951. Some thoughts on distribution of earnings. *Oxford Ecnomic Papers,* Volume 3, pp. 135-145.

Saatkamp, B. D., Masera, O. R. & Kammen, D. M., 2000. Energy and health transitions in development: fule use, stove technology and morbidity in Jaracuaro, Mexico. *Energy for Sustainable Development,* p. Volume IV No.2.

Samad, H. A., Khandker, S. R., Asaduzazaman, M. & Yunus, M., 2013. The Benefits of Solar Home Systems: An Analysis from Bangladesh. *World Bank Policy research working paper 6724,* p. The World bank.

Semple, S., Apsley, A., Wushishi, A. & Smith, J., 2014. Commentary: Switching to biogas e What effect could it have on indoor air quality and human health?. *biomass and bioenergy,* pp. 125-129.

Short S, Bashir H, Marshall P, Miller N, Olmschenk D, Prigge K, Solyntjes L, 2017. *Diagnosis and Treatment of Respiratory Illness in Children and Adults,* s.l.: Institute for Clinical Systems Improvement. .

Sianesi, B., 2004. An Evaluation of the Active Labor Market Programmes in Sweden. *The review of Economics and Statistics,* 86(1), pp. 133-155.

Smith, J. & Todd, P., 2005. Does Matching Overcome Lalonde's Critique of Nonexperimental Estimators?. *Journal of Econometrics,* 125(1-2), pp. 305-353.

Smith, K. R. et al., 2013. Energy and Human Health. *Annual Review of Public Health,* 16 January, pp. 159-188.

Smith, K. R. et al., 2011. Effect of reduction in household air pollution on childhood pneumonia in Guatemala (RESPIRE): a randomised controlled trial. *The Lancet 378* , p. 1717–26.

Squires, T., 2015. *THE IMPACT OF ACCESS TO ELECTRICITY ON EDUCATION AND OTHER ESSAYS IN SPATIAL ECONOMICS: PHD THESIS,* Rhode Island: Brown University.

SRINIVASAN, S. & CARATTINI, S., 2016. Adding fuel to fire? social spilll overs and spatial disparities in the adoption of LPG in India. *Version, Novemebr 24,* , pp. Research Paper 48, Centre for International environmental studies, Graduate Institute Geneva.

SRINIVASAN, S. & CARATTINI, S., 2016. ADDING FUEL TO FIRE? SOCIAL SPILLOVERS AND SPATIAL DISPARITIES IN THE ADOPTION OF LPG IN INDIA. *Swiss Network for international studies* , pp. Research paper 48, November, 2016.

The National Bureau of Statistics [Tanzania], 2017. *National Environment Statistics Report,* Dar es Salaam, Tanzania Mainland: s.n.

Titcombe, M. E. & Simcik, M., 2011. Personal and indoor exposure to PM2.5 and polycyclic aromatic hydrocarbons in the southern highlands of Tanzania: a pilot-scale study. *Enviro monit assess,* pp. 461-476.

Troncoso, K., Armendáriz, C. & Alatorre, S., 2013. Improved cook stove adoption and impact assessment: A proposed methodology. *Energy Policy,* p. 637–645.

United Republic of Tanzania, 2016. *Tanzania National Panel report (NPS)- Wave 4, 2014-2015,* Dar-es-salaam: National Bureau of Statistics.

USAID, 2017. *Family Planning and Reproductive Health- Tanzania,* Newyork: USAID.

Vahlne, N. & Ahlgren, E. O., 2014. Policy implicationsforimprovedcookstoveprograms—A casestudy of the importance of village fuel use variations. *Energy Policy,* p. 484–495.

Van de Walle, D., Ravallion, M., Mendiratta, V. & Koolwal, G., 2015. Long-Term Impacts of Household Electrification in Rural India. *World Bank Economic Review,* Volume lhv057.

van Dijk, K. A. L. & Clancy, J., 2010. Impacts of Electricity Access to Rural Enterprises in Bolivia, Tanzania and Vietnam. *Energy for Sustainable Development 14,* p. 14–21.

WHO, 2016. *World Health organization.* [Online]
Available at: http://www.who.int/mediacentre/factsheets/fs292/en/

Yip, F. et al., 2017. Assessment of traditional and improved stove use on household air pollution and personal exposures in rural western Kenya. *Environment International,* p. 185–191.

Young, H. P., 2009 . Innovation Diffusion in Heterogeneous Populations: Contagion, Social Influence, and Social Learning. *American Economic Review 99:5,* p. 1899–1924.

Yu, F., 2011. Indoor Air Pollution and Children's Health: Net Benefits from Stove and Behavioral Interventions in Rural China. *Environ Resource Econ* , p. 495–514.

APPENDICES

APPENDIX A

Table 1: Definition and measurement of outcomes

Outcome	Definition and Measurement	Measurement
Total energy expenditure	The total amount in Tshs used on Charcoal, electricity, LPG and kerosene in the last month	Tanzania Shillings (Tshs)
Kerosene Expenditure	The total amount in Tshs used on kerosene in the last month	Tanzanian Shillings (Tshs)
Charcoal Expenditures	The total amount in Tshs used on Charcoal in the last month	Tanzanian Shillings (Tshs)
Modern energy budget	The total amount in Tshs used on LPG and Electricity in the last month	Tanzanian Shillings (Tshs)
Traditional energy budget	The total amount in Tshs used on kerosene and charcoal in the last month	Tanzanian Shillings (Tshs)
Modern budget share	Ratio of the modern budget to the total budget	Ratio
Traditional budget share	Ratio of the traditional budget to the total budget	Ratio
Evening study hours	Number of hours Children between 5 and 20 uses to study at night in a week	Hours
Education years	Years of education for children between 5 and 20 years of age	Years of Education
Standard seven exam result	The passing of the standard seven exam for children over grade 7	-
Acute respiratory symptoms	If a household has at least one child under the age of 5 and below with self-reported acute respiratory symptoms (fever, cough and short breaths emanating from the chest and nasal area)	-
Number of children below five years	The number of children below 5 years old in a household	-
Number of births in last five years	The number of births to a woman in a household in the last five years	-
Waiting period between pregnancies	The period between two consecutive births	Years
Contraceptive use	If a woman is contraceptive as a family planning method	-

Table 2: The number and percentage of households using modern cooking fuels

Modern energy use	Full sample	Urban sample	Rural sample
Yes	112 (3.35%)	91 (8.3%)	3 (0.17%)
No	3232 (96.65%)	1,005 (91.7%)	1767 (99.83%)
Total	3,344	1,094	1770

Source: Authors own calculations from the Tanzanian National Panel data survey wave 4

Table 3: The balance of covariates for the full sample before and after matching using NPS Wave 4

Variable	Unmatched Matched	Mean			t-test	
		Treated	Control	%bias	t	p>t
Sex of the household head	U	0.76786	0.71256	12.6	1.27	0.203
	M	***0.76852***	***0.78739***	***-4.3***	***-0.33***	***0.740***
Age of house hold head	U	42.161	44.505	-15.9	-1.63	0.104
	M	***41.593***	***41.244***	***2.4***	***0.19***	***0.851***
Age of the household head squared	U	1986	2205.7	-15.1	-1.52	0.129
	M	***1918.4***	***1881.7***	***2.5***	***0.21***	***0.836***
Household size squared	U	19.964	32.146	-33.7	-2.79	0.005
	M	***20.102***	***21.633***	***-4.2***	***-0.52***	***0.606***
Household uses a clean stove	U	0.91964	0.05229	348.1	40.20	0.000
	M	***0.91667***	***0.90197***	***5.9***	***0.37***	***0.708***
Education of the household head	U	13.705	6.5699	163.6	16.78	0.000
	M	***13.648***	***13.631***	***0.4***	***0.03***	***0.977***
Household Income	U	15.942	14.936	137.1	14.48	0.000
	M	***15.904***	***15.879***	***3.4***	***0.27***	***0.789***
House ownership status	U	0.30357	0.68657	-82.7	-8.59	0.000
	M	***0.31481***	***0.30802***	***1.5***	***0.11***	***0.915***

Table 4: The balance of covariates for the urban sample before and after matching using NPS Wave 4

Variable	Unmatched Matched	Mean		%bias	t-test	
		Treated	Control		t	p>t
Sex of the head of household	U	0.74725	0 .67099	16.8	1.49	0.136
	M	***0.74359***	***0.76829***	***-5.4***	***-0.36***	***0.722***
Age of household head	U	40.374	41.074	-5.0	-0.47	0.642
	M	***41.91***	***41.308***	***4.3***	***0.28***	***0.779***
Household size	U	15.22	20.142	-24.8	-1.97	0.049
	M	***16.833***	***17.682***	***-4.3***	***-0.36***	***0.722***
Household has access to electricity	U	.94505	.61316	87.2	6.43	0.000
	M	***.9359***	***.91928***	***4.4***	***0.40***	***0.691***
Household owns a biomass stove	U	1.2198	1.1216	26.2	2.67	0.008
	M	***1.0897***	***1.0829***	***1.8***	***0.15***	***0.880***
Household owns a Clean stove	U	.94505	.09571	322.0	26.80	0.000
	M	***.9359***	***.93599***	***-0.0***	***-0.00***	***0.998***
Education of the household head	U	14.275	8.4018	142.7	12.92	0.000
	M	***13.859***	***13.876***	***-0.4***	***-0.02***	***0.980***
	U	16.023	15.278	109.2	10.14	0.000

Household Income	***M***	***16.03***	***16.026***	***0.6***	***0.04***	***0.972***
House ownership status	U	.20879	.37288	-36.6	-3.14	0.002
	M	***.23077***	***.24513***	***-3.2***	***-0.21***	***0.834***

Table 5: The balance of covariates for the full sample before and after matching using THDS 2015/16

Variable	Unmatched (U) Matched (M)	Mean		%bias	t-test	
		Treated	Control		t	p>t
Household has access to electricity	U	.94253	.29543	90.8	6.15	0.000
	M	***.94118***	***.94025***	***0.1***	***0.01***	***0.991***
Education of woman in the household	U	1.977	.97258	161.8	14.72	0.000
	M	***1.9529***	***1.9404***	***2.0***	***0.13***	***0.895***
Household size	U	5.023	6.3985	-51.9	-4.12	0.000
	M	***5.0353***	***5.1006***	***-2.5***	***-0.20***	***0.841***
Household size squared	U	29.598	50.576	-40.8	-2.87	0.004
	M	***29.765***	***30.506***	***-1.4***	***-0.17***	***0.863***
Wealth index	U	4.9655	2.9408	204.6	13.61	0.000
	M	***4.9647***	***4.9088***	***5.6***	***0.98***	***0.327***
Household owns a mobile	U	.96552	.48519	127.6	8.95	0.000
	M	***.96471***	***.95323***	***3.0***	***0.37***	***0.708***
Household's frequency of listening to the radio	U	1.3103	1.1532	19.7	1.82	0.069
	M	***1.3412***	***1.3528***	***-1.5***	***-0.10***	***0.923***
Woman's age	U	30.138	29.987	2.4	0.19	0.849
	M	***30.118***	***30.155***	***-0.6***	***-0.04***	***0.965***
Occupation of the household head	U	4.9195	5.3238	-10.8	-0.92	0.357
	M	***5.0118***	***5.0896***	***-2.1***	***-0.15***	***0.881***
Sex of the household head	U	1.2184	1.1744	11.1	1.07	0.284
	M	***1.2118***	***1.2176***	***-1.5***	***-0.09***	***0.927***
Age of the household head squared	U	1467.9	1757.6	-28.0	-2.28	0.023
	M	***1476.6***	***1455.3***	***2.1***	***0.16***	***0.869***

Table 6: The balance of covariates for the urban sample before and after matching using the THDS 2015/16

Variable	Unmatched Matched	Mean		%bias	t-test	
		Treated	Control		t	p>t
Household has access to electricity	U	.97333	.62958	47.6	2.95	0.003
	M	***.97183***	***.95426***	***2.4***	***0.17***	***0.867***
Education of the household's wife	U	1.9467	1.2571	110.0	9.10	0.000
	M	***1.8873***	***1.8767***	***1.7***	***0.10***	***0.917***

Household size	U	5	5.915	-36.5	-2.72	0.007
	M	***5.0563***	***5.0952***	***-1.5***	***-0.11***	***0.915***
Household head owns a mobile	U	.96	.74499	63.5	4.25	0.000
	M	***.95775***	***.94538***	***3.7***	***0.34***	***0.734***
Age of the household head	U	36.627	39.618	-27.5	-2.10	0.036
	M	***36.944***	***37.146***	***-1.9***	***-0.12***	***0.905***
Sex of the household head	U	1.2133	1.1852	7.0	0.61	0.542
	M	***1.1972***	***1.2192***	***-5.5***	***-0.32***	***0.748***
Household listens to radio	U	1.3333	1.3642	-4.0	-0.35	0.728
	M	***1.3803***	***1.3543***	***3.4***	***0.20***	***0.843***
Household watches Television	U	1.88	1.1555	106.3	7.37	0.000
	M	***1.8732***	***1.8335***	***5.8***	***0.51***	***0.611***
Age of the household head's wife	U	29.6	29.15	7.4	0.57	0.572
	M	***29.606***	***29.683***	***-1.3***	***-0.08***	***0.935***

Table 7: Propensity score estimation for impact of expenditure analysis

VARIABLES	(1) Full sample	(2) Urban sample
sex of household head	0.0856	0.00140
	(0.300)	(0.360)
age of household head	-0.0883	-0.00124
	(0.0560)	(0.0139)
hhsize_2	-0.0150**	-0.0368***
	(0.00735)	(0.0121)
access to electricity		0.428
		(0.609)
RECODE of owns_biomass		1.325***
		(0.491)
Cleanstove	4.261***	4.404***
	(0.406)	(0.527)
edu_headyrs2	0.0835**	0.0523
	(0.0342)	(0.0439)
logexpmR	0.657***	0.807**
	(0.238)	(0.327)
house_ownership2	-0.720**	-0.419
	(0.304)	(0.416)
age_head2	0.00100*	
	(0.000561)	
Constant	-13.96***	-19.15***
	(3.488)	(4.807)
Observations	3,344	1,094

Table 8: Propensity score estimation for the health outcomes impact analysis

VARIABLES	(1) full_sample	(2) Urban_sample
Household has: electricity	-0.0577	0.283*
	(0.187)	(0.159)
Highest educational level	1.168***	1.340***
	(0.206)	(0.210)
Number of household members (listed)	-0.212	-0.192***
	(0.232)	(0.0744)
hhsize_2	0.000910	
	(0.0169)	
Wealth index	3.209***	
	(0.605)	
Owns a mobile telephone	0.960	0.871
	(0.610)	(0.618)
Frequency of listening to radio	-0.553***	-0.583***
	(0.158)	(0.171)
Respondent's current age	0.0262	0.0491**
	(0.0229)	(0.0248)
occupation_head2	-0.0799**	
	(0.0393)	
Sex of household head	-0.212	-0.0748
	(0.316)	(0.332)
age_head2	4.40e-05	
	(0.000174)	
Age of household head		-0.0131
		(0.0164)
Frequency of watching television		1.485***
		(0.334)
Constant	-19.57***	-7.564***
	(3.088)	(1.147)
Observations	5,557	1,522

Table 9: Matching quality Indicators for the impact of household use of modern cooking fuels analysis

	NPS WAVE 4		**THDS**	
	Full sample	**Urban Sample**	**Full Sample**	**Urban Sample**
Before Matching				
Pseudo R2	0.549	0.558	0.395	0.241
P>chi2	0.000	0.000	0.000	0.000
Mean of standardised bias	101.1	85.6	68.1	45.5
After Matching				
Pseudo R2	0.002	0.004	0.006	0.003
P>chi2	1.000	1.000	1.000	1.000

Mean of standardised bias	3.1	2.7	2.0	3.0

Table 10: The impact of Household's use of modern cooking fuels on energy expenditures

Outcome variable	Full Sample		Urban sample	
	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias
Total energy expenditure	11208.7 (6934.113)	n.s	11439.47 (6262.8)	n.s
Modern energy budget expenditure	26473.74*** (6452.638)	(+)>2	29028.22 *** (7510.3)	(+) >2
Charcoal expenditure	-14021.79*** (2143.328)	(-)>2	-16317.63*** (2893.87)	(-)>2
Modern energy budget share	0.319066*** (0.0382703)	(+)>2	0.3071832*** (0.0415919)	(+)>2
Traditional energy expenditure	-15265.04*** (2657.838)	(-)>2	-17588.75*** (2780.49)	(-)>2
Traditional energy share	-0.338059*** (0.0378087)	(-)>2	-0.3408712*** (0.0434521)	(-)>2

Table 11: The impact of household's use of modern cooking fuels on health

Outcome variable	Full sample		Urban sample	
	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias
Respiratory disease symptoms (either of the symptoms)	0.0889674 (0.0665996)	n.s	0.0482069 (0.0658801)	n.s
Respiratory disease symptoms (all symptoms)	-0.0215508** (0.0101316)	>2	-0.0240931** (0.0115776)	>2
Has cough	0.0615478 (0.0667622)	n.s	0.0511097 (0.0589013)	n.s
Has fever	0.0323645 (0.0487019)	n.s	-0.0196987 (0.0562317)	n.s
Has short breaths and chest problem emanating from the chest	-0.007846 (0.0234023)	n.s	-0.0073439 (0.026283)	n.s
Cough and short breaths	-0.0137449 (0.0173658)	n.s	- 0.014523 (0.0235643)	n.s
Fever and cough	-0.0255522** (0.0098592)	>2	- 0.0276492 ** (0.0119801)	>2
Fever and shorth breaths	0.0058143 (0.0422442)	n.s	0.000789 (0.0308697)	n.s

Figure1: The common support and Propensity score imbalance before and after matching for the full sample (Impact of household's use of cooking fuels on energy expenditures)

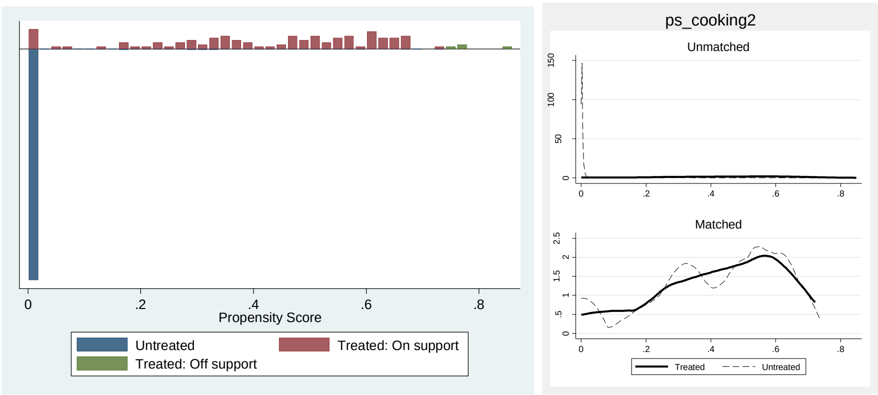


Figure 2: The common support and Propensity score imbalance before and after matching for the urban sample (Impact of household's use of cooking fuels on energy expenditures)

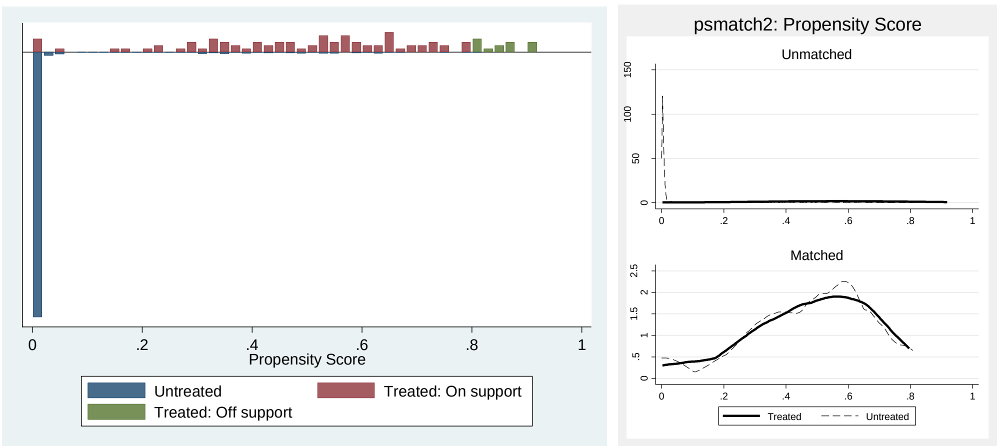


Figure 3: The common support and Propensity score imbalance before and after matching from the full sample (Impact of household's use of cooking fuels on health)

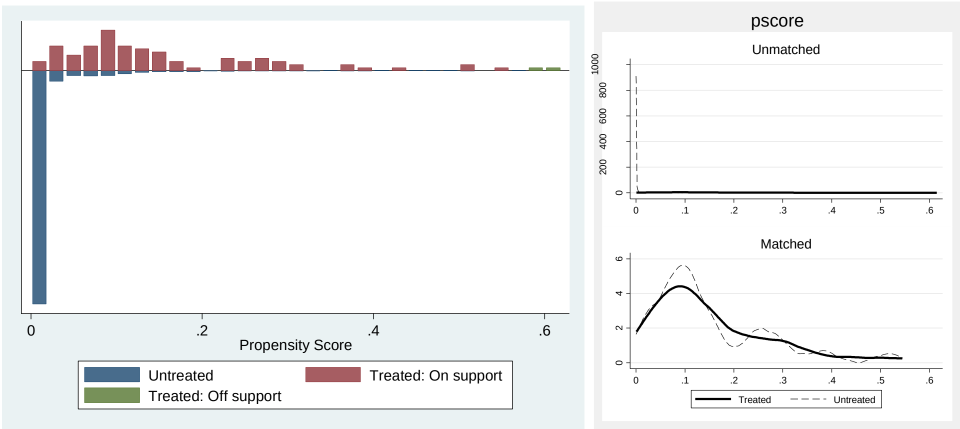
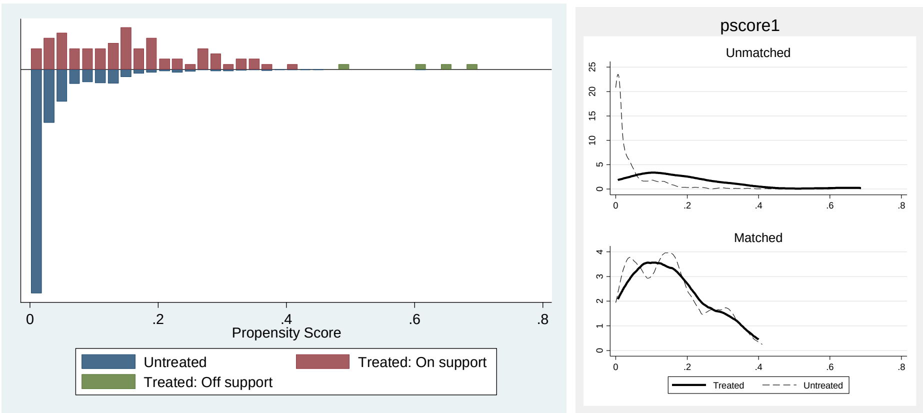


Figure 4: The common support and Propensity score imbalance before and after matching for the urban sample (Impact of household's use of cooking fuels on health)



APPENDIX B

Table 12: The number and percentage of electrified households in Tanzania

Electrified	Full sample	Urban sample	Rural sample
Yes	1,284 (38.40%)	704 (64.35 %)	325 (18.36%)
No	2,060 (61.60 %)	390 (35.65%)	1,445 (81.64%)
Total	3,344	1,094	1770

Source: Authors own calculations from the Tanzanian National Panel data survey wave 4

Table 13: The balance of covariates before and after matching for the full sample using NPS wave 4

Variable	Unmatched Matched	Mean		%bias	t-test	
		Treated	Control		t	p>t
Sex of household head	U	.74533	.69515	11.2	3.13	0.002
	M	***.74207***	***.74367***	***-0.4***	***-0.09***	***0.929***
Age of household head	U	42.439	45.665	-22.0	-6.08	0.000
	M	***42.419***	***42.123***	***2.0***	***0.53***	***0.596***
Household size	U	29.037	33.422	-10.5	-2.72	0.007
	M	***28.79***	***29.139***	***-0.8***	***-0.24***	***0.807***
Education of the household head	U	9.2648	5.2782	94.1	26.83	0.000
	M	***8.7763***	***8.5562***	***5.2***	***1.35***	***0.177***
Income of the Household	U	15.405	14.698	107.2	30.06	0.000
	M	***15.323***	***15.332***	***-1.3***	***-0.35***	***0.728***
House ownership status	U	.50467	.77913	-59.7	-17.17	0.000
	M	***.52003***	***.51827***	***0.4***	***0.09***	***0.931***
Household floor materials	U	.86293	.29806	139.5	38.04	0.000
	M	***.85309***	***.84752***	***1.4***	***0.38***	***0.702***
Household wall materials	U	.62695	.16456	107.3	31.12	0.000
	M	***.60267***	***.5968***	***1.4***	***0.29***	***0.769***
Household’s number of dwelling rooms	U	2.8388	2.5927	17.5	5.04	0.000
	M	***2.7604***	***2.725***	***2.5***	***0.59***	***0.558***
Occupation of the head of the household	U	.2391	.67913	-98.4	-27.39	0.000
	M	***.25459***	***.25986***	***-1.2***	***-0.29***	***0.768***

Table 14: The balance of covariates before and after matching for the rural sample using NPS wave 4

Variable	Unmatched Matched	Mean		%bias	t-test	
		Treated	Control		t	p>t
Sex of the household head	U	.77538	.71142	14.7	2.33	0.020
	M	***.77329***	***.78591***	***-2.9***	***-0.39***	***0.700***
Age of household head	U	44.252	46.122	-12.2	-1.95	0.052
	M	***44.289***	***45.286***	***-6.5***	***-0.87***	***0.383***
Household size	U	39.96	37.269	5.0	0.79	0.432
	M	***40.102***	***42.36***	***-4.2***	***-0.57***	***0.570***
Education of household head	U	7.2369	4.9197	58.2	9.72	0.000
	M	***7.1988***	***6.9522***	***6.2***	***0.78***	***0.436***

Household Income	U	15.134	14.61	79.4	12.85	0.000
	M	***15.125***	***15.13***	***-0.8***	***-0.10***	***0.919***
House ownership status	U	.78769	.86228	-19.7	-3.40	0.001
	M	***.79193***	***.80139***	***-2.5***	***-0.30***	***0.766***
Floor material	U	.56308	.1474	96.3	17.60	0.000
	M	***.55901***	***.55296***	***1.4***	***0.15***	***0.878***
Wall material	U	.14462	.01592	48.7	11.12	0.000
	M	***.13665***	***.13526***	***0.5***	***0.05***	***0.959***
Number of dwelling rooms in the house	U	3.28	2.7163	37.6	6.85	0.000
	M	***3.2764***	***3.2856***	***-0.6***	***-0.07***	***0.943***
Occupation of household head	U	.68308	.85121	-40.5	-7.23	0.000
	M	***.68944***	***.70009***	***-2.6***	***-0.29***	***0.770***

Table 15: The balance of covariates before and after matching for the urban sample using NPS wave 4

Variable	Unmatched Matched	Mean		%bias	t-test	
		Treated	Control		t	p>t
Sex of household head	U	.70597	.62564	17.1	2.73	0.006
	M	***.69333***	***.6814***	***2.5***	***0.45***	***0.656***
Household size	U	20.051	19.156	4.0	0.62	0.536
	M	***19.16***	***20.044***	***-4.0***	***-0.68***	***0.493***
Education of household head	U	10.125	6.6615	84.7	13.26	0.000
	M	***9.12***	***9.0097***	***2.7***	***0.55***	***0.584***
Household Income	U	15.538	14.983	86.0	13.54	0.000
	M	***15.388***	***15.378***	***1.6***	***0.31***	***0.756***
House ownership status	U	.3054	.45641	-31.4	-5.04	0.000
	M	***.32***	***.32493***	***-1.0***	***-0.18***	***0.855***
Floor material	U	.95597	.66667	79.5	14.04	0.000
	M	***.94833***	***.94726***	***0.3***	***0.08***	***0.933***
Wall material	U	.7571	.50256	54.6	8.84	0.000
	M	***.73167***	***.72118***	***2.2***	***0.41***	***0.684***
Main dwelling room number	U	2.4844	2.1821	21.7	3.37	0.001
	M	***2.2833***	***2.3056***	***-1.6***	***-0.27***	***0.786***
occupation2_head	U	.09233	.21282	-34.0	-5.66	0.000
	M	***.09667***	***.11291***	***-4.6***	***-0.92***	***0.359***

Table 16: The balance of covariates before and after matching for the full sample using THDS 2015/16

Variable	Unmatched Matched	Mean		%bias	t-test	
		Treated	Control		t	p>t
Age of the head of the household	U	39.771	40.165	-3.2	-1.17	0.244
	M	**39.771**	**39.697**	**0.6**	**0.21**	**0.836**
Education years of the head of the household	U	8.1919	5.9458	57.4	21.14	0.000
	M	**8.1919**	**8.018**	**4.4**	**1.46**	**0.145**
Household size	U	48.869	51.177	-3.5	-1.25	0.213
	M	**48.869**	**48.757**	**0.2**	**0.05**	**0.959**
Households listens to the radio	U	1.3573	1.0202	43.5	15.77	0.000
	M	**1.3573**	**1.3819**	**-3.2**	**-1.10**	**0.270**
Household watches Television	U	1.0067	.36687	85.4	32.39	0.000
	M	**1.0067**	**1.01**	**-0.4**	**-0.13**	**0.897**
Household own a mobile phone	U	.68202	.36536	66.8	24.35	0.000
	M	**.68202**	**.66685**	**3.2**	**1.08**	**0.279**
Occupation of the household head	U	5.6691	5.0798	14.4	5.32	0.000
	M	**5.6691**	**5.7838**	**-2.8**	**-0.66**	**0.510**

Table 17: The balance of covariates before and after matching for the rural sample using THDS 2015/16

Variable	Unmatched Matched	Mean		%bias	t-test	
		Treated	Control		t	p>t
Age of the household head	U	41.202	40.401	6.3	1.89	0.058
	M	**41.146**	**41.181**	**-0.3**	**-0.07**	**0.942**
Education of the household head	U	7.1994	5.7772	37.4	11.31	0.000
	M	**7.1906**	**7.1611**	**0.8**	**0.20**	**0.845**
Household size	U	55.319	53.336	2.8	0.82	0.413
	M	**54.991**	**53.583**	**2.0**	**0.55**	**0.583**
Household listens to the radio	U	1.2795	1.0014	35.5	10.55	0.000
	M	**1.2784**	**1.2779**	**0.1**	**0.02**	**0.988**
Household watches Television	U	.66541	.33099	48.4	15.47	0.000
	M	**.66339**	**.67029**	**-1.0**	**-0.23**	**0.820**
Household owns a mobile phone	U	.56571	.32853	49.1	14.91	0.000
	M	**.56505**	**.56073**	**0.9**	**0.22**	**0.823**
Occupation of the household head	U	5.2311	4.8974	8.9	2.60	0.009
	M	**5.2277**	**5.3013**	**-2.0**	**-0.38**	**0.701**

Table 18: The balance of covariates before and after matching for the rural sample using THDS 2015/16

Variable	Unmatched Matched	Mean Treated	Control	%bias	t-test t	p>t
Age of the household head	U	37.694	38.749	-9.3	-1.70	0.089
	M	**37.319**	**36.828**	**4.3**	**0.97**	**0.333**
Education of the household head	U	9.6327	6.9578	70.2	12.29	0.000
	M	**9.4333**	**9.4612**	**-0.7**	**-0.15**	**0.878**
Household size	U	39.503	38.213	2.8	0.48	0.629
	M	**36.243**	**34.564**	**3.6**	**0.86**	**0.392**
Household watches Television	U	1.5022	.58228	127.5	22.35	0.000
	M	**1.4823**	**1.4871**	**-0.7**	**-0.13**	**0.893**
Household owns a mobile phone	U	.85088	.5865	61.5	11.44	0.000
	M	**.84493**	**.82362**	**5.0**	**1.20**	**0.230**
Occupation of the household head	U	6.3048	6.1751	3.2	0.51	0.608
	M	**6.3489**	**6.5313**	**-4.5**	**-0.93**	**0.354**

Table 16: Propensity score estimation for impact of electrification on expenditure, education and time use analysis using the NPS wave 4.

VARIABLES	(1) Full sample	(2) Rural sample	(3) Urban sample
sex of household head	-0.133	-0.0152	-0.236
	(0.109)	(0.173)	(0.165)
age of hosuehold head	0.00175	-0.00708	
	(0.00388)	(0.00543)	
hhsize_2	-0.0027**	-0.00311*	-0.00279
	(0.00137)	(0.00169)	(0.00408)
edu_headyrs2	0.102***	0.0473**	0.139***
	(0.0132)	(0.0208)	(0.0215)
logexpmR	1.013***	0.907***	0.932***
	(0.0929)	(0.135)	(0.158)
house_ownership2	-0.474***	-0.0658	-0.774***
	(0.124)	(0.213)	(0.213)
floor_material2	1.407***	1.263***	1.620***
	(0.123)	(0.159)	(0.257)
wall_material2	0.450***	1.115***	0.160
	(0.119)	(0.302)	(0.184)
Number of habitable rooms	0.169***	0.129**	0.227***
	(0.0402)	(0.0516)	(0.0787)
occupation of household head	-0.327***	-0.279	0.359
	(0.122)	(0.181)	(0.257)
Constant	-17.37***	-15.40***	-16.36***
	(1.347)	(1.941)	(2.273)
Observations	3,344	1,770	1,094

Table 20: Propensity score estimation for impact of electrification on health and fertility analysis using 2015/16 THDS.

VARIABLES	(1) Full sample	(2) Rural sample	(3) Urban sample
Age of household head	0.00484*	0.00704**	0.00237
	(0.00277)	(0.00303)	(0.00692)
Education of household head	0.0897***	0.0694***	0.133***
	(0.00877)	(0.0101)	(0.0193)
hhsize_2	0.00127**	0.00102*	0.00406**
	(0.000511)	(0.000525)	(0.00167)
Frequency of listening to radio	0.156***	0.192***	
	(0.0419)	(0.0476)	
Frequency of watching television	0.789***	0.456***	1.285***
	(0.0434)	(0.0539)	(0.0866)
Owns a mobile telephone	0.789***	0.707***	0.712***
	(0.0643)	(0.0725)	(0.155)
occupation_head2	0.0173**	0.0116	0.0204
	(0.00730)	(0.00841)	(0.0149)
Constant	-2.487***	-2.367***	-2.688***
	(0.149)	(0.164)	(0.365)
Observations	5,556	4,170	1,386

Table 21: Matching quality indicators for the impact of household use of electricity

	NPS WAVE 4			**THDS**		
	Full sample	**Rural sample**	**Urban Sample**	**Full Sample**	**Rural sample**	**Urban Sample**
Before Matching						
Pseudo R2	0.350	0.204	0.239	0.166	0.081	0.268
P>chi2	0.000	0.000	0.000	0.000	0.000	0.000
Mean of standardised bias	66.7	41.2	45.9	39.2	26.9	45.7
After Matching						
Pseudo R2	0.001	0.002	0.001	0.001	0.000	0.001
P>chi2	0.941	0.999	0.996	0.542	0.998	0.737
Mean of standardised bias	1.6	2.8	2.3	2.1	1.0	3.1

Table 22: The impact of Household electrification on energy expenditures

Variable	Full sample		Rural sample		Urban sample	
	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias
Total energy expenditure	9893.955*** (1165.712)	>2	1422.522 (932.8858)	n.s	10138.22*** (2148.402)	(+)1.9-2
Kerosene expenditure	-2584.472*** (419.283)	>2	-1332.175*** (244.8063)	>2	-2593.641*** (629.1626)	>2
Traditional energy expenditure	-2663.905 ** (1067.379)	(-) 1.5-1.6	-1472.504** (688.1512)	>2	-4155.893** (1655.772)	(-) 1.4-1.5
Modern energy budget	12557.86*** (623.516)	>2	2895.026*** (527.3982)	(+)1-1.1	14228.05*** (812.6543)	>2
Modern energy budget share	0.3254351*** (0.0099871)	>2	0.1418945*** (0.0212963)	(+)1-1.1	0.3587903*** (0.012536)	>2
Traditional energy budget share	-0.342115*** (0.016201)	>2	-0.265999*** (0.0315396)	>2	-0.332957*** (0.0190764)	>2

Table 23: Impact of household electrification on education outcomes

Variable	Full sample		Rural sample		Urban sample	
	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias
Study hours	1.223128*** (0.3837315)	(+) 1-1.1	0.6913118* (.3809661)	(+)1-1.1	2.4149 *** (0.5623059)	(+)1.8-1.9
Study hours (boys)	1.129013** (0.4787241)	(+) 1-1.1	0.5569739 (0.4753587)	n.s	1.955508** (0.7395021)	(+) 1.3-1.4
Study hours (girls)	1.456541*** (0.3401197)	(+) 1-1.1	0.7090958 (.592498)	n.s	2.748634** (0.7162748)	(+)1.3-1.4
Education years	0.3773642** (0.1743501)	(+) 1-1.1	0.4681123** (0.2323217)	(+)1.1-1.2	0.1882237 (0.2970063)	n.s
Education years (boys)	0.1084777 (0.2009645)	n.s	0.1307921 (0.2678974)	n.s	-0.2805175 (0.4037532)	n.s
Education years (girls)	0.790234** (0.2867365)	(+) 1.3-1.4	0.445853 (0.2928733)	n.s	0.8642235** (0.4250708)	(+) 1.2-1.3
Standard seven results	0.0461815 (0.0345554)	n.s	0.0448727 (0.0398655)	n.s	0.0041256 (0.0367256)	n.s
Standard seven result (boys)	0.0575483** (0.0200828)	(+) 1-1.1	0.0562661* (0.0330455)	1-1.1	0.0032038 (0.0323413)	n.s
Standard seven result (girls)	0.0136894 (0.0313936)	n.s	0.0170192 (0.0430219)	n.s	0.0290464 (0.0254471)	n.s

Table 24: Impact of household electrification on Time use

Variable	Full sample		Rural sample		Urban sample	
	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias
Households with members that spent most time in non-agricultural activities	0.0220952 (0.0149526)	n.s	0.0659021* (0.0359631)	1.2-1.3	0.0034423 (0.0232322)	n.s
Households with members (**males**) that spent most time in non-agricultural activities	0.0079506 (0.0244616)	n.s	0.0460192 (0.0359359)	n.s	-0.0052356 (0.0471116)	n.s
Households with members(**females**) that spent most time in non-agricultural activities	-0.0154152 (0.0322714)	n.s	0.0334557 (0.0330912)	n.s	-0.0224913 (0.0433133)	n.s

Table 25: The impact of household electrification on health

Variable	Full sample		Rural sample		Urban sample	
	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias
Respiratory disease symptoms (all symptoms)	-0.003393452 (0.0042342)	n.s	-0.0021 (0.0038931)	n.s	-0.0140607 (0.011516)	n.s
Cough and short breaths	0.003008062 (0.005459)	n.s	-0.003002 (0.0052821)	n.s	0.0041833 (0.0171726)	n.s
Fever and cough	-0.00147335 (0.0046904)	n.s	-0.000796196 (0.004394)	n.s	-0.0105669 (0.0171649)	n.s
Fever and shorth breaths	-0.000142111 (0.0141709)	n.s	0.009648216 (0.0129775)	n.s	-0.0658699 (0.0401211)	n.s
Has cough	0.000715273 (0.0161367)	n.s	-0.002358233 (0.0161817)	n.s	-0.0307068 (0.050841)	n.s
Has fever	-0.001882035 (0.0182442)	n.s	-0.002135854 (0.0184388)	n.s	-0.0327933 (0.0497409)	n.s

Has short breaths and chest problem emanating from the chest	0.005763224 (0.0057896)	n.s	-0.00224566 (0.0055556)	n.s	0.0107004 (0.0149089)	n.s
Respiratory disease symptoms (either of the symptoms)	-0.00227678 (0.0182748)	n.s	-0.015833108 (0.0157848)	n.s	-0.0006148 (0.0610377)	n.s

Table 26: Impact of household electrification on fertility

Variable	Full sample		Rural sample		Urban sample	
	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias	ATT	Critical Γ hidden bias
Number of children under five	-0.04459 (0.0324771)	n.s	-0.0281987 (.0405474)	n.s	-0.0266878 (0.0776173)	n.s
Number of births in last five years	-0.0299082 (0.024246)	n.s	-0.0192053 (0.0213274)	n.s	-0.0491348 (0.0615992)	n.s
Prefered waiting time before next pregnancy	0.0295344 (0.0220463)	n.s	0.029057* (.0161902)	(+) 1.4-1.5	-0.0060244 (0.0530191)	n.s
Use of contraceptives	0.0442699 ** (0.0199879)	(+) >2	0.0061785 (0.0190849)	n.s	0.0959578 * (0.0490053)	(+) 1.4-1.5

Figure 5: The common support and Propensity score imbalance before and after matching for the full sample (The Impact of household electrification on non-health outcomes)

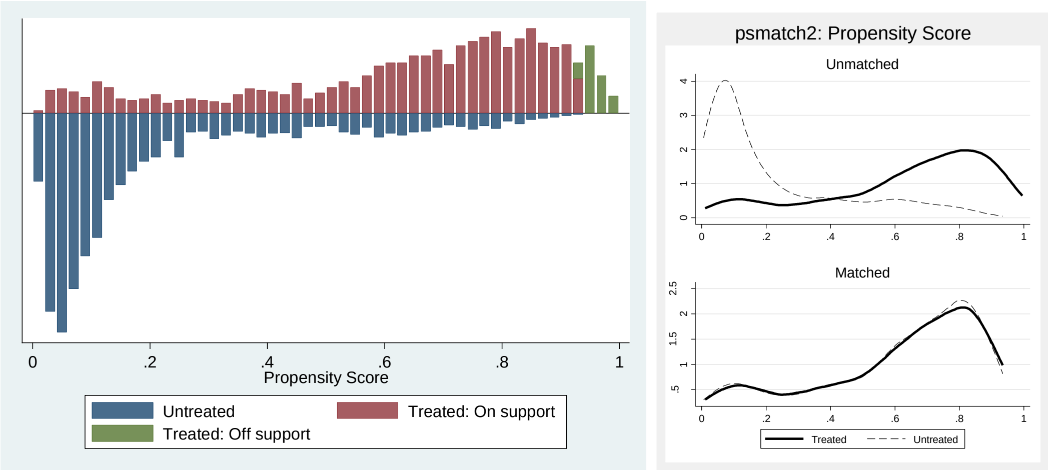


Figure 6: The common support and Propensity score imbalance before and after matching for the rural sample (The Impact of household electrification on non-health outcomes)

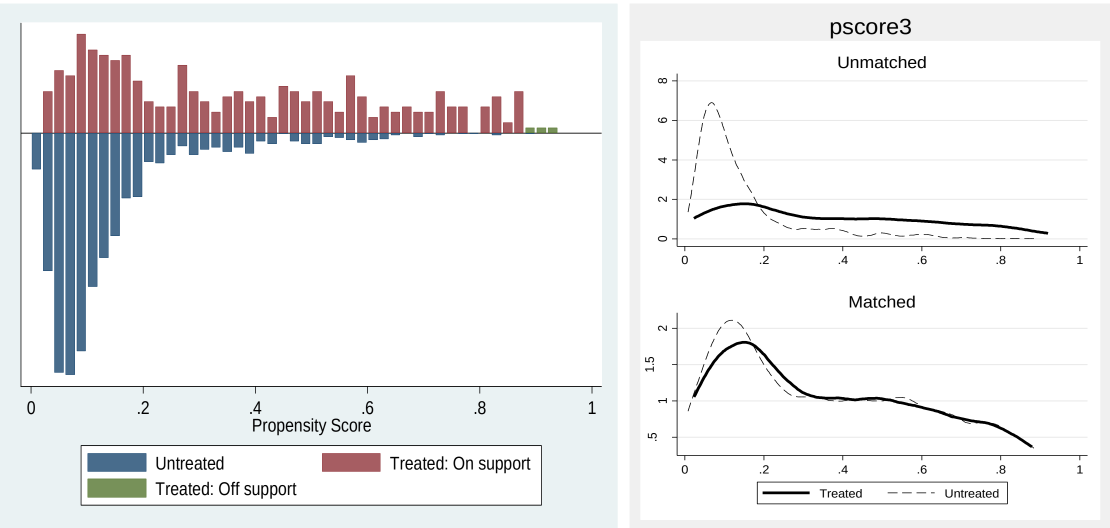


Figure 7: The common support and Propensity score imbalance before and after matching for the urban sample (The Impact of household electrification on non-health outcomes)

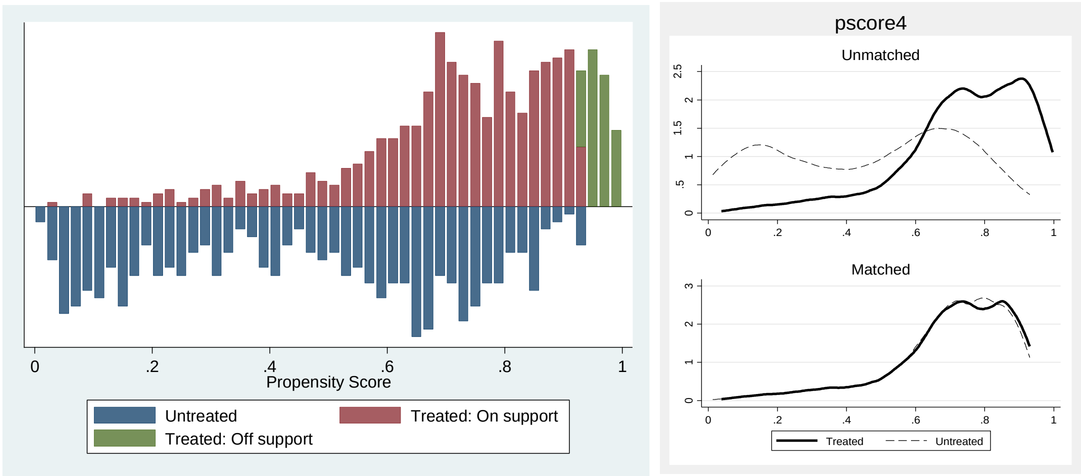


Figure 8: The common support and Propensity score imbalance before and after matching for the full sample (The Impact of household electrification on health outcomes)

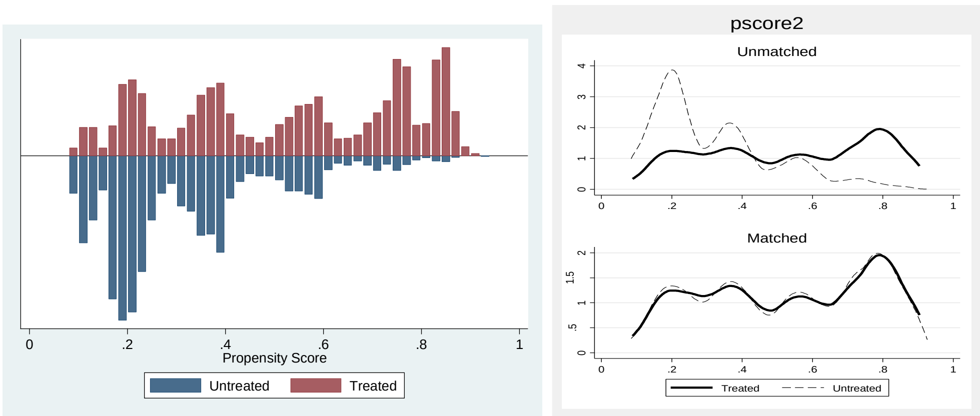


Figure 9: The common support and Propensity score imbalance before and after matching for the rural sample (The Impact of household electrification on health outcomes)

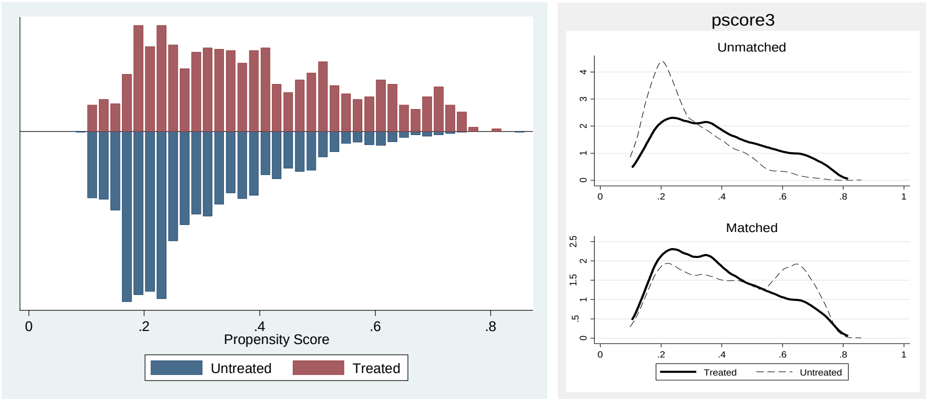


Figure 10: The common support and Propensity score imbalance before and after matching for the urban sample (The Impact of household electrification on health outcomes)