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Social protection schemes in rural Rwanda: A panacea for household energy burdens?

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ABSTRACT

The role of social protection programs in low-income countries is increasingly becoming a subject of interest on the development agenda in the public discourse. The literature reveals a diversity of findings about the role of social protection on household development outcomes. There is little documentation regarding how social protection schemes affect household energy burdens in rural areas, especially in Sub-Saharan Africa. Rwanda is one of the African countries that have taken deliberate steps to institutionalize the provision of social protection schemes to its citizenry. Therefore, this paper examined how accessibility to different social protection schemes affected household energy burdens in rural Rwanda using nationally representative household-level microdata (EICV5). Results from the Lewbel Instrumental Variable Estimator, nearest neighbor matching, and Inverse Probability Weighted Regression Adjustment showed that Vision 2020 Umurenge and Girinka social protection schemes significantly negatively affected household energy cost burdens. These study findings suggest that social protection schemes may require other efforts or policy instruments that might encourage use of modern energy services to address energy affordability barriers in rural areas.

Introduction

Access to modern energy services positively impacts household well-being (Andadari et al., 2014). Achieving the Sustainable Development Goal number 7 (SDG 7) target by 2030 remains an uphill task for the Global South. Meanwhile, most developing countries strive to provide affordable access to modern energy services to improve the socio-economic development of their citizens, either through grid electricity connections or off-grid energy options (Palit & Kumar, 2022; Winkler et al., 2011). However, modern commercial energy services come at an opportunity cost, which attracts an economic burden that might force households to trade off other consumption opportunities to fulfil their energy needs (Alkon et al., 2016).

Literature shows that low-income households often face the challenge of high or low energy cost burdens driven by various reasons. Some reasons fueling high energy burdens include housing characteristics, energy efficiency, geographical differences, and social and economic status in Mexico (Molar-Cruz et al., 2022). Furthermore, Chen et al. (2022) found that the energy burden was more noticeable in poor counties that consisted of older people, the needy, disabled persons and racialized persons who do not have health insurance in the United States of America. However, little is documented on household energy cost burden from the Global South perspective and whether social protection programs can help address this growing challenge for the rural populace. This paper examined the effect of the accessibility of social protection schemes on the energy cost burden in rural Rwanda using the nationally representative household-level microdata (EICV5).

The current study defined the energy burden as a share of energy expenditures in total household expenditures expressed in percentage form and is used in literature as one of the objective metrics to assess the affordability of energy services (Alkon et al., 2016; Molar-Cruz et al., 2022). The other question of how high a share is 'unaffordable' remains an open-ended empirical question. In the developed country contexts (i.e., the United States of America), some scholars have used the threshold of 6 % as a cut-off point to label high household energy cost burden, which may be somehow arbitrary (Brown et al., 2020; Chen et al., 2022; Colton, 2011). It is tricky for developing country contexts to adopt such a threshold for various reasons unilaterally. For instance, a high share of

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fuel expenses for a household in the developing world may imply massive fuel consumption because of big family size, limited use of energy-efficient appliances, expensive energy prices or high electricity tariffs, or poor income levels (Winkler et al., 2011). Other scholars opted to use subsistence level of energy needs (i.e., use price reduction per efficient kilowatt-hour), which differ depending on climate and prevailing economic conditions (Foster et al., 2000; Winkler et al., 2011). This study did not look at such a detailed level of investigation due to limited data availability.

High energy cost burdens force low-income households to change between competing basic household needs such as food, housing, health care costs and others (Brown et al., 2020; Memmott et al., 2021). Such trade-offs can plunge households into a more dire situation. On the other hand, low energy burdens may also imply that low-income families may choose to prioritize other expenditures more than others for different reasons, i.e., as part of an energy efficiency strategy (Brown et al., 2019; Herrero, 2017; Molar-Cruz et al., 2022).

Therefore, this study strived to answer the following public policy research question: how do social protection programs influence the energy cost burden or energy consumption of rural households, especially in the Global South? In other words, what is the mediating role of social protection programs to accelerate SDG 7, which aims at universal access to affordable, reliable and modern energy services by 2030? These remain two open empirical questions yet to be fully understood in different low-income country contexts. Therefore, this paper assessed the effect of two social protection schemes' access (the Vision 2020 Umurenge program and the Girinka program) on household energy burdens in rural Rwanda. This paper utilized energy burden (share of fuel expenditures in total household expenditures) to investigate energy affordability for rural households in Rwanda (Bohr & McCreery, 2020; Charlie et al., 2016; Molar-Cruz et al., 2022; Ross et al., 2018). The study findings revealed that these two social protection schemes negatively affect rural household energy burdens.

Literature review

Energy poverty, energy burdens and social protection schemes

Energy poverty remains a global challenge phenomenon, with almost 85 % of 789 million persons living without electricity in their homes, particularly those residing in parts of the world (also termed as the "last mile" population) (UNSD, 2020; Zaman et al., 2021a). This phenomenon has no universal definition, yet other scholars have defined it as a constraint in access and affordability of modern energy services, particularly electricity (Jiang et al., 2020; Zaman et al., 2021a). On the other hand, the last mile population are economically poor coupled with limited assets. As a result, they have difficulties breaking free from structural poverty and social inequalities exacerbated by a lack of direct access to essential infrastructures (Dulal & Shah, 2014; Oum, 2019; Zaman et al., 2021a).

Worse still, Laborde, Martin, & Vos, 2021 further projected that the recent COVID -19 pandemic could raise extreme poverty in Sub-Saharan Africa (15 % for rural residents) and (44 % for urban residents) using the benchmark of $1.90 per person per day international poverty line in terms of Purchasing Power Parity (PPP) which has implication on energy consumption. These projections were made with no social and economic mitigation policy instruments, i.e., fiscal stimulus and expansion of social safety nets as a working assumption in their global model scenario analysis. In addition, Loayza and Pennings (2020) documented a macroeconomic impact of an income loss of about 220 billion United States dollars associated with the COVID -19 pandemic in the Global South. In general, the post-COVID-19 Pandemic economic global outlook remains bleak, with the possibility of decelerating the progress of attaining the 2030 United Nations Sustainable Development Goals (SDGs), particularly SDG 7, which is the central pillar of the rest of the SDGs (Barbier & Burges, 2020; IRENA, 2020). The COVID -19 pandemic disrupted the supply chains and consumer income (i.e., 30 million people who initially lost electricity access due to affordability challenges in 2020), thereby widening the energy access gap (IRENA, 2021). Much more effort is required to close this energy access gap. Recent projections show that 660 million people might not have direct electricity access, and 2.4 billion people might not have clean cooking technologies in 2030 (IRENA, 2020).

Social protection systems consist of contributory schemes (i.e., social insurance, public works) and non-contributory social assistance schemes (i.e., social cash transfers) (World Bank, 2018). On the other hand, ILO (2017) defined social protection systems as a set of policies and programs formulated to deal with poverty and vulnerability challenges. Devereux (2002) hypothesized that social safety nets would have protection and promotion effects on the lives of the poor. Using three southern African case studies (Namibia, Zambia, Mozambique), Devereux (2002) found that the poor invested the income from social safety nets in small-scale businesses, education, social network, and purchasing productive assets that eventually led to chronic poverty reduction.

Moreover, energy safety nets are a form of social assistance that governments mainly initiate to give financial support to the poor and vulnerable groups so that they access modern energy services through connection or actual energy consumption by way of dealing with the affordability challenges at the prevailing energy market prices (SEALL, 2020). However, not all social protection systems that are globally implemented have incorporated the energy access component. Some countries like Kenya, India and Brazil specifically implemented what is referred to as energy safety nets to target and support people that face energy poverty. Most countries have implemented what is referred to as social safety nets which are just government-led social assistance that gives financial support to the poor and vulnerable groups to deal with poverty and inequality and does not require any contribution from the beneficiaries (World Bank, 2018). But how is social protection linked to Energy? Mary Robinson Foundation suggested that social protection systems be used to accelerate the process of expanding modern energy services to the last mile population in the countries (MRFCJ, 2016; SEALL, 2020). There is little documentation regarding how social protection mechanisms affect access to modern energy services. What is the mediating role of social protection programs in the energy cost burden of rural households in low-income countries?

Theoretical explanations

In the theory of change, social protection schemes come in different shapes as 'anti-poverty' tools. These include social cash transfers or, sometimes, more complex programs aimed at addressing several underlying problems of uninsured shocks, liquidity constraints, information failures or a combination of all (Gertler et al., 2012; Rema & Karlan, 2016). Conceptually, participation in social protection programs translates into an income level adjustment and affects energy consumption in several ways. Due to the diversity in prevailing conditions in the study context, it might not be easy to establish the role of social protection schemes on energy burdens. Beneficiaries of social protection schemes may spend less time at home using clean energy fuels (Twumasi, Jiang, Ameyaw, Danquah, & Acheampong, 2020). Sometimes, due to illiteracy, lack of awareness and delayed payments, rural residents may incur unnecessary debts (Twumasi, Jiang, Ameyaw, Danquah, & Acheampong, 2020). Failure to switch from traditional to modern fuels may worsen their energy poverty status (Katutsi, Dickson, & Migisha, 2020; van Rooyen, Stewart, & de Wet, 2012). Another view is that access to social protection schemes is linked to improved wealth status (income levels) of the rural beneficiaries through increased capacities to buy clean fuels, which proved unattainable before becoming beneficiaries (Chakrabarti & Handa, 2023). This view resonates well with the energy ladder hypothesis, which stipulates that an increase in income triggers a switch in energy consumption of rural dwellers from traditional energy sources to modern energy sources (Ajayi, 2018). A contrary postulation, termed “fuel stacking”, posits that as their wealth status improves (income level increases), rural residents may diversify their energy source base but not necessarily abandon traditional fuels (Chakrabarti & Handa, 2023; Lokonon, 2020; Nawaz & Iqbal, 2020). Again Akpalu et al. (2011) and Lokonon (2020) noted that prevailing energy prices and the availability of other energy sources affect the dynamism in usage patterns of biomass energy.

So far, there are few scholarly works on how social assistance measures influence access to modern energy services, especially in low-come countries (MRFCJ, 2016). Employing the panel data analytical techniques, Chakrabarti & Handa, 2023 examined how ultra-poor households in rural areas adapted their energy portfolios when experiencing exogenous income increases from unconditional cash transfer programs in Malawi and Zambia. Their study revealed that families made several changes to primary fuel sources frequently after receiving 3 to 4 years of cash transfers. Specifically, households were making more adjustments to lighting fuels (i.e., from firewood to torches) than cooking fuels. Similarly, Nawaz and Iqbal (2020) analyzed the impact of the Benazir Income Support Program (unconditional cash transfer program) on fuel choices among ultra-poor households in Pakistan by employing a regression discontinuity design using two rounds of household-level data. Their study found that unconditional cash transfers increased the use of modern fuels among the beneficiaries and encouraged the use of intermediate fuels and, in other circumstances, even traditional fuels. In other words, social protection schemes like unconditional cash transfers can potentially encourage interfuel substitution among poor households.

Furthermore, Hanna and Oliva (2015) also explored the effect of a non-governmental organization asset transfer program (two cows, four goats, one cow and one goat, or a non-farm enterprise) on the fuel consumption choices of the poor in India. Their study revealed mixed findings regarding the role of social protection schemes on fuel choices. First, Hanna and Oliva (2015) that an increase in assets led to a rise in the use of electricity as the primary lighting source. However, for some households, the program also increased the use of kerosene (observed an increase in kerosene expenditures). Regarding cooking fuels, Hanna and Oliva (2015)) found that households did not switch to better cooking sources; instead, they opted for readily available dirty sources (i.e., dung from livestock).

The relevance and contribution of this study are timely, considering that energy access may improve the socio-economic conditions of households by increasing their resilience during this post-COVID-19 pandemic era, and energy access goes beyond just grid connection but also the affordability of such energy services, including the off-grid energy options (Zaman et al., 2021b). For instance, Zaman et al. (2021b) highlighted multiple benefits of accessing modern forms of energy, such as reducing indoor pollution associated with the heavy use of dirty fuels and also available electricity may help in phone charging and communication through telehealth services. As such, accessibility to a wide range of social protection schemes may help break the affordability challenge of many rural households with limited solvency (Grimm et al., 2020; Sievert & Steinbuks, 2020; Zaman et al., 2021b). Meanwhile, Molar-Cruz et al. (2022) used energy burden to characterize energy affordability for urban households in Mexico, paying attention to electricity and gas consumption. Their study finding revealed vast differences in energy consumption, energy burdens and energy use. Such differences were attributed to different socio-economic and geographical factors. Molar-Cruz et al. (2022) reiterated that there is no one-size-fits-all energy policy solution.

As already pointed out (SEALL, 2020) regarding energy connections, efforts to ensure that the poor and vulnerable groups get grid connections, LPG connections, or other off-grid energy options are the most important step towards energy access. Still, they do not necessarily lead to the actual consumption of clean fuels because of the affordability challenge. Policymakers ought to know that targeting mechanisms for energy safety nets may differ depending on the ultimate goal, whether to only consumption or connection to clean cooking technology or national grid electricity coupled with the need for advanced analysis of household energy consumption and expenditure to inform policy direction. Support for electricity connections or clean cooking technology distribution may be a necessary first step towards energy access but does not guarantee that energy is affordable or consumed by the most vulnerable among the population. Finally, SEALL (2020) hinted that each country needs to design an appropriate social protection mechanism or energy safety nets that should suit the country's context. The designing process ought to take into consideration of gender, geographical, institutional and economic factors so that these social protection programs or energy safety nets ought to evolve with time to adapt to socio-economic dynamics.

The study context: energy agenda and social protection in Rwanda

Rwanda formulated a road map for boosting both on-grid and off-grid energy solutions in 2021 through its National Electrification Plan (NEP) and Rural Electrification Strategy (RES) (EDCL, 2021; MININFRA, 2015, 2016). The Energy Development Corporation Limited (EDCL) champions the implementation of the NEP and RES through straightforward programs such as Electricity Access Roll Out Program (EARP) and Rwanda Universal Energy Access Program (RUEAP) with financial support from the government and collaborating Development partners. Rwanda intends to achieve universal electricity access by 2024, where 52 % of the population has a national grid connection, whilst 48 % will utilize off-grid energy solutions, i.e., microgrids and solar home systems (EDCL, 2021).

As of January 2022, Rwanda's national cumulative electricity access rate stood at 68 %, with approximately 48.8 % of the population connected to the national grid. Meanwhile, 19.7 % of the population uses off-grid energy solutions, particularly solar (REG, 2022). The government of Rwanda has also prioritized off-grid energy solutions as the most cost-effective means to close the electricity access gap, particularly for the rural parts of the country, so that a target of 70 % from the national grid and 30 % from off-grid solar is achieved by 2024 (MINIFRA, 2016; REG, 2022). The country made strides in selling off-grid solar lighting products (mainly multi-light and solar home systems), especially towards the end of 2019, due to PAY Go sales mechanisms (GOGLA, 2022a, 2022b). However, the recent reports in the country conducted by the Energy Private Developers association (EPD) indicated that the supply of off-grid electricity is constrained by affordability challenges, especially for low-income households who are failing to service payments in this post-COVID 19 pandemic era (GOGLA, 2022a).

On the other hand, Rwanda adopted its vision 2050 in December 2015, aiming to become an upper-middle-income country by 2035 and eventually a high-income nation by 2050 (BTI, 2022; GoR, 2020). The country's poverty statistics show a decline in poverty levels from 60 % in 2001 to 37 % in 2017, attributed solely to the development of Kigali city, which has a poverty rate of about 13.8 % (BTI, 2022). However, the country faces a challenge of inequalities. For instance, the income of the wealthiest 10 % is 3.2 times higher than that of the poorest 40 % (BTI, 2022).

Rwanda has achieved milestones concerning improving citizens' welfare and poverty alleviation, particularly in recent decades. Its economy grew steadily at 6.9 % between 2001 and 2016, increasing the gross domestic product per capita values (World Bank, 2016). The rapid economic growth rate is an enabler of Rwanda's fiscal space. With assistance from other development partners, it has been able to implement a National Social Protection Strategy (NSPS) since 2005. The latest National Social Protection Policy attracts a budgetary allocation in the range of Frw 121,000,000,000 every fiscal year from 2020 to 2024 (Republic of Rwanda, 2020). The latest policy is more inclusive to broad categories of vulnerable groups. It also focuses more on social assistance than humanitarian interventions, as in the past decade. The newly instituted policy document highlights a formal definition of social protection as follows:

"*All public and private income transfer schemes, social care services, livelihood support and insurance schemes that, together, ensure that all extremely poor and vulnerable people have income security, a dignified standard of living and are protected against life cycle and livelihood risks to achieve sustainable graduation and self-reliance (Republic of Rwanda, 2020) pp. ix)*".

The operational scope of social protection in Rwanda is determined by four pillars, as shown in Fig. 1 from the newly instituted National Social Protection Policy (Republic of Rwanda, 2020). Fig. 1 depicts various elements that constitute four principles central to Rwanda's vision for social protection. Firstly, the concept is designed to achieve security by providing essential support services to impoverished people. The aim is to help them avert the worst consequences of poverty. In this case, the support is provided through social assistance programs and core social protection programs such as direct support, public works, disability allowance and others. Secondly, the Rwandan vision of social protection focuses on prevention by putting in place safety nets that keep people from falling into poverty. Rwandan social protection is achieved through tailor-made intervention, including social security schemes, community health insurance, and long-term saving schemes. The third principle points to promotional interventions. In this regard, poor people receive investment support so that they are in a position to lift themselves out of poverty and eliminate the need to receive social protection. The last principle has to do with transformation, which implies that the social protection scheme has to improve the socioeconomic status of society in general. The transformation aspect is attained by promoting positive values, respect for rights and family and other community-based support systems through creating labour market opportunities, particularly imperfect labour markets. However, this study focused only on beneficiaries of two selected social protection schemes: the Vision 2020 Umurenge Program and the Girinka (one cow, one family) program.

In terms of population size, the country's population is projected to reach 16.3 million by 2032 (NISR, 2014). As with most Sub-Saharan African countries, about 80 % of the Rwandan population is rural. Essentially, they rely on agriculture-based livelihoods and are characterized by high poverty levels, estimated at 44 %, higher than 6 % for their urban-dwelling counterparts (NISR, 2016). In 2006, the government of Rwanda came up with intervention measures in the form of an asset transfer program code-named "one cow per poor family program", popularly identified as Girinka. The poorest households received dairy cows to uplift their well-being through locally available nutritious foodstuffs (Nilsson et al., 2019). Livestock is considered a valuable asset that helps build resilience against economic shocks. In addition, cow dung serves as fuel and a traditional decoration symbol in Rwandan homes, apart from being used for making beehives (Nkusi, 2014). So far, the country's statistical data showed that 300 thousand dairy cows have been distributed since its inception and projected to 350 thousand dairy cows by 2017 (Nilsson et al., 2019).

On the other hand, the original Vision 2020 Umurenge Programme (VUP) started in 2008 as documented by Kidd and Kabare (2019) and LODA (2016) with three main pillars namely: (i) Direct support (unconditional monthly cash transfers) that targeted households that had limited labor capacity (had no adult aged between 18 and 64 years that work) and also those classified under Ubudehe Category 1 (collapsing the Ubudehe categories 1 and 2 previously there were six Ubudehe categories); (ii) Classic Public works (i.e. short-term, temporary employment on community infrastructure and environmental projects) and expanded public works (i.e. part-time work for at least 2 h per day, could be multi-year or year-round employment to cater for those having care taking responsibility) likewise targeted those households that fell in Ubudehe Category 1 and had some labour capacity; (iii) Financial services targeted those who had been on the public works program and were deemed credit worthy to be given small loans at very low interest rate such that they could engage in different small scale businesses. However, the updated VUP program document comprises four main

Fig. 1. Operation scope of social protection in Rwanda.
Adapted from the Republic of Rwanda (2020).

pillars, namely; (i) the safety net component; (ii) livelihoods enhancement; (iii) shock responsive social protection; and (iv) Sensitization and Public Communications, which is aligned to the Rwanda National Social Protection Policy (LODA, 2022; MINALOC, 2020). Other social protection schemes include an old age grant scheme that excludes VUP and is mainly for urban areas. In addition, there are also other schemes such as the genocide survivors' support and assistance program, the Rwanda Social Security Scheme, the Rwanda Demobilization and Reintegration and food relief which are being implemented in Rwanda (Gatzinsi et al., 2019; Kidd & Kabare, 2019; LODA, 2022).

Meanwhile, no previous study has investigated the relationship between social protection schemes' access and the rural energy cost burden in Rwanda. What is not yet clear is the impact of social protection schemes' access on energy cost burden within the developing country context in a rural set up. Therefore, the empirical evidence in this paper contributes to the current literature on why social protection schemes might be necessary to break energy affordability barriers in rural spaces. Firstly, this paper utilizes energy burden as a proxy measure of energy affordability following Molar-Cruz et al. (2022), who characterized the energy burden of urban households in Mexico. Secondly, using the most recent cross-sectional household dataset from Integrated Living Standard Surveys such as EICV5 in Rwanda may pave the way for exploring patterns and comparisons that can easily be tested over time and across countries implementing similar programs.

Materials and methods

Source of data

The study utilized household responses from a 2016/2017 Household Living Conditions Survey (EICV5), with special permission from the National Institute of Statistics of Rwanda (NISR). The Enquête Integrals les Conditions de Vie des Ménages (EICV 5) is a nationally representative sample built on the previous household living condition surveys which started in 2001. It is known by the French acronym “Enquête Integrals les Conditions de Vie des Ménages (EICV1)” and is done regularly. The EICV5 datasets contain various information that captures welfare indicators, access to essential services, housing and utilities, and information on different social protection schemes available to households. We did not get the baseline information for these social protection schemes, which limited us in choosing the empirical model. The descriptive statistics of the study variables are highlighted in Table 1. A total of 12,006 households with complete responses constituted the total rural sample for the study. The survey questionnaire captured levels of earnings and expenditures at the household level. Dwelling characteristics and housing conditions were also included. The micro-dataset was collected and managed NISR in collaboration with World Bank. The NISR employed a national master sampling frame to select the sample villages in each district. Sample villages were systematically selected within each district, where probability was proportional to size (PPS). More so, the measure of size was based on the number of households in each village, obtained from the 2012 Census frame and other details are found in the survey report by the National Institute of Statistics of Rwanda (NISR, 2018).

Dependent variable

Energy cost burden measure

This study computed energy cost burden as the share of energy expenditures in total household expenditures (x_{HI}) expressed in percentage form to get the energy burden, as depicted in Eq. (1). The annual household energy expenditures were a total sum of self-reported energy expenses incurred on electricity (x_{elec}), charcoals (x_{char}), batteries ($x_{battery}$), candles (x_{candl}), fuelwood (x_{wood}) and kerosene ($x_{kerosene}$), excluding energy costs for transport. This paper used the non-binary measure of the energy burden (Molar-Cruz et al., 2022) as expressed in Eq. (1) instead of using the 6 % cut-off point as is the case in the Global North (Brown et al., 2020; Colton, 2011) to assess the affordability aspect of modern energy services. The study findings are critical to inform policy makers in terms of finding long lasting solutions for the domestic sector to cope with the energy cost burden amidst worsening economic conditions due to COVID-19 pandemic, especially in rural areas. The mathematical formulation of the household energy cost burden (HEB) was expressed in percentage form as follows (Alkon et al., 2016; Molar-Cruz et al., 2022):

$$HEB = \left(\frac{x_{elec} + x_{char} + x_{battery} + x_{candl} + x_{wood} + x_{kerosene}}{x_{HI}}\right) \times 100\% \quad (1)$$

Table 1
Summary of descriptive statistics.

Variable	Definition	Mean	SD
Household energy burden	The ratio of annual household energy expenditures to annual household total consumption	1.914	3.48
Girinka (One cow, one family-asset transfer)	Dummy 1 = yes, 0 = No	0.083	0.276
VUP program access	Dummy 1 = yes, 0 = No	0.139	0.346
Sex of household head	Dummy 1 = male head, 0 = female	0.739	0.438
Poor	Dummy 1 = yes, 0 = Non poor	0.376	0.484
Age of household head	Years	46.14	15.77
The household head has no formal education	Dummy 1 = yes, 0 = otherwise	0.29	0.45
The household head has primary education	Dummy 1 = yes, 0 = otherwise	0.64	0.48
The household head has secondary education	Dummy 1 = yes, 0 = otherwise	0.05	0.23
The household head has tertiary education	Dummy 1 = yes, 0 = otherwise	0.01	0.11
Tenancy-rented house	Dummy 1 = yes, 0 = otherwise	0.08	0.27
One room-house	Dummy 1 = yes, 0 = otherwise	0.23	0.42
Household size	Number of persons	4.45	2.04
Head has disability	Dummy 1 = yes, 0 = otherwise	0.06	0.23
Share of “able-bodied” adults (16–64 years)	Number-continuous	0.55	0.24
Share of dependents (<16 years & >65 years)	Number-continuous	0.47	0.24
Kigali Province	Dummy 1 = Kigali, 0 = otherwise	0.03	0.17
Southern Province	Dummy 1 = Southern, 0 = otherwise	0.28	0.45
Western Province	Dummy 1 = Western, 0 = otherwise	0.24	0.43
Northern Province	Dummy 1 = Northern, 0 = otherwise	0.17	0.38
Eastern Province	Dummy 1 = Eastern, 0 = otherwise	0.25	0.43

Independent variables

Following (Gatzinsi et al., 2019), observable factors used for nearest-neighbor matching to assess the effect of the VUP social protection schemes include the household composition, disability status, and wealth using the Ubudehe wealth ranking (housing index). On the other hand, eligibility criteria to access the Girinka (one cow, one family) social protection program depends on access to pasture, province, and access to land, total livestock units computed following (Njuki et al., 2011) especially the number of cows, household wealth using the Ubudehe wealth ranking (Nilsson et al., 2019; Nkusi, 2014). Other independent variables used in the econometric analysis include housing characteristics. Specifically, the study utilized household responses regarding the demographics such as sex of household head, age and education level of the household.

Treatment variable

Households in the sample reported whether they benefited from any of several country's specific social protection programs, such as the Girinka program, Vision 2020 Umurenge Program (direct support, public works, financial services), and food relief. This study mainly focused on the beneficiaries of two social protection programs (restricted to households that received cash or in-kind support from Vision 2020 Umurenge Program and the Girinka program). So, the treatment variable is in binary form, taking the value of 1 if they benefited from the social protection program and zero otherwise.

Descriptive statistics of the sample

The summary statistics for the main variables and controls used for this paper are presented in Table 1 and are highlighted based on beneficiary status (those who had access to the social protection schemes and those who did not have access). Specifically, this study focused only on beneficiaries of selected social protection schemes: - Vision 2020 Umurenge program (13.9 % of the whole sample) and One cow per family, commonly known as Girinka (8.3 % of the whole sample).

Empirical modelling

Participation in social protection programs demands that beneficiaries meet specific minimum requirements specified by the government and some organizations, which poses a selection bias problem. For instance, Rwandan beneficiaries of the Vision 2020 Umurenge Programme (VUP) are selected based on community wealth ranking known as "Ubudehe" and other criteria. Ubudehe is a system of household wealth ranking implemented across Rwanda (LODA, 2022). In some cases, beneficiaries of the VUP schemes may not be randomly assigned due to non-eligibility as stipulated by the VUP program document and other reasons. Secondly, Kidd & Kabare, 2019 observed that the main implementation challenge of the VUP public works scheme was the mismatch, i.e., households with limited labour capacities or severe disabilities ended up being enlisted in the VUP Public works instead of being enrolled on VUP DS. In response to this anomaly, the government of Rwanda has further incorporated an "expanded" public works program to cater for those households who face caretaking responsibilities (LODA, 2022). Expanded public works focus on less intensive labour, such as tree planting, cleaning public spaces and many others (LODA, 2022). As such, the past VUP selection process was not random. It might be seen as a form of rationing instead of targeting in some cases due to the high exclusion of eligible households or persons, i.e., disabled persons (Gatzinsi et al., 2019; Kidd & Kabare, 2019; LODA, 2022).

On the other hand, opportunity costs may limit households from participating in some social protection programs. As such, a behavioral response might be formulated under a random utility theoretical framework, whereby rural households are faced with a set of options and constraints simultaneously (Martey et al., 2021; Muhammad, Mugera, & Schilizzi, 2018; Nilsson et al., 2019). For instance, to qualify for the Girinka program in Rwanda, which is government sponsored, it requires the household to meet a particular criterion such as having no cow, having a piece of land, having access to pasture and demonstrating good husbandry practices, among others (Nilsson et al., 2019). To address these challenges, other scholars have opted to employ mixed methods to get more insights into the impacts of the VUP social protection program. For example, Gatzinsi et al. (2019) used mixed method techniques and found that institutions remain vital players that influence the accessibility of the VUP schemes and related asset transfer program. In addition, they also found that on the part of the beneficiaries, what matters is the household composition, gender power dynamics, disability, care responsibilities, marital arrangements, intrahousehold communication, plus access to other social programs.

Still more, the literature provides several quasi-experimental techniques (i.e., Randomized controlled trials, Different in Different estimation, Regression Discontinuity Design, Propensity Score Matching, Inverse Probability Weighted Regression Adjustment) to deal with the problems of selection bias and non-randomness (Habimana, Haughton, Nkurunziza, & Haughton, 2021; Hill et al., 2021; Martey et al., 2021; Nawaz & Iqbal, 2021). Noting that the implementation of these social protection schemes may face the challenge of poor compliance, voluntary enrollment, or universal coverage, the current study opted to use the Lewbel Instrumental Variable approach (Lewbel, 2018). This method utilizes internal instruments instead of external instruments in the social protection literature, which may fall short of the validity test (Bastardoz et al., 2023; Mwale et al., 2022). The strength of this approach lies in the fact that it can isolate effects of interest by using heteroscedasticity in the available data without external instruments (Lewbel, 2018). In other words, using the internally generated instruments has two advantages as pointed out by Bastardoz et al. (2023). Firstly, internally generated instruments help to assess causal identification in design and research questions whenever good external instruments are complicated or impossible to find. Secondly, the researcher has the added advantage of comparing results from using internally generated instruments and the results from using the traditional external instruments as a way of testing the validity of external instruments and boost the confidence of the study findings (Bastardoz et al., 2023; Hopp & Pruschak, 2020). The drawback of using internally generated instruments is that researchers cannot have theoretical justification and only depend on untestable assumption and this is why researchers are encouraged to use external instruments if they are available (Bastardoz et al., 2023; Baum & Lewbel, 2019a).

As such, looking at the available EICV5 dataset, it was challenging to get traditional instruments that would predict the outcome variable (energy cost burden) while satisfying exclusion restrictions. The advantage of using the Lewbel Instrumental Variable approach is that it exploits heteroskedasticity in mismeasured or endogenously explanatory variables to construct instrument variables (Baum & Lewbel, 2019a, 2019b; Lewbel, 2018; Saroj, 2021). The Lewbel econometric technique is discussed as follows: mathematical notations are maintained as in Lewbel (2018) and Mwale et al. (2022).

Suppose we have a sample that comprises endogenous variables Y_1 (depicts energy cost burden variable) and Y_2 (depicts social protection scheme variable, i.e., VUP direct support, VUP public works, VUP financial services, Girinka asset scheme) and a set of control variables X. Our goal was to compute the effect of the social protection scheme (δ) and the set of β in the following models. In general, the ideal model to be estimated would be the Ordinary Least Squares (OLS) model, which is depicted in Eq. (2).

$$Y_i = \beta_0 + \beta_i X_i + \mu_i \tag{2}$$

where X_i is a vector of exogenous regressor or endogenous regressor and μ_i depicts the random error term for the ith observation, which captures unobservable, unknown, unmeasured, and omitted variables that would also influence the dependent variable (Y_i). However, OLS regression works well when all the explanatory variables are exogenous, implying that they have zero covariance with the random error term (μ_i). Mathematically, it implies that the $Corr\,(X_i, \mu_i) = 0$ or $Cov\,(X_i, \mu_i) = 0$. On the other hand, if there is an endogenous regressor in Eq. (2), it implies that its $Corr\,(X_i, \mu_i) \neq 0$ *or* $Cov\,(X_i, \mu_i) \neq 0$. The social protection scheme variables may be endogenous due to different reasons (i.e., measurement errors, simultaneity and others) as discussed in the literature (Gatzinsi et al., 2019; Kidd & Kabare, 2019; Mwale et al., 2022; Nilsson et al., 2019; Saroj, 2021). Thus, why the Lewbel Instrumental variable approach was employed in this study to handle the endogeneity problem and is further illustrated using Eqs. (3) and (4).

$$Y_1 = X'\beta + Y_2\delta + \varepsilon_1 \tag{3}$$

$$Y_2 = X^{'}\alpha + \varepsilon_2 \quad (4)$$

where disturbance term ε_1 and disturbance term ε_2 in Eqs. (3) and (4) could be correlated. Therefore, in the first stage, the Lewbel estimator computed α by regressing Y_2 on X. The second stage involved computing predicted residuals $\widehat{\varepsilon}_2 = Y_2 - X^{'}\widehat{\alpha}$. The internal instrument (depicted by Z could be part of all the control variables represented by set X. As such, to get δ and β, involved using a two-stage least squares regression of Y_1 on Y_2 and X which was now being replaced by $(Z - \overline{Z})\widehat{\varepsilon}_2$ but now as internal instruments. $\overline{Z}$ is the sample mean of Z. The internal instrument satisfies the usual standard assumptions of the classic instrument variable, which are:

(i) $E(X\varepsilon_1) = 0$, $E(X\varepsilon_2) = 0$ and $E(XX^{'})$ is non-singular; (ii) $Cov(Z, \varepsilon_1\varepsilon_2) = 0$, and) $Cov(Z, \varepsilon_2^2) \neq 0$. In this study, the endogenous regressor took a binary form. Eq. (4) gave heteroskedastic errors and met all the assumptions as stipulated in the Lewbel et al. (2012) and Lewbel (2018) papers. The estimation of the Lewbel estimator was done using the Stata command "Ivreg2h" in the Stata version 15 statistical software (Baum et al., 2012; Lewbel, 2018; Lewbel et al., 2012; Mwale et al., 2022; Saroj, 2021). Nevertheless, for robustness testing, the study also implemented matching algorithms such as nearest neighbor matching and other quasi-experimental econometric techniques (i.e., Inverse probability weighted regression adjustment, inverse probability weights) after coarsening the data sets. The coarsening process was done following Blackwell et al. (2009), Iacus et al. (2012), Lewbel (2018) and Nilsson et al. (2019) using the cem Stata command in Stata version 15 statistical software. The inverse probability weighted regression adjustment (IPWRA), which is also termed a doubly robust estimator, accounts for the similarity between the treated and the control group in terms of the distribution of observable factors rather than the unobservable to get the Average Treatment Effect (ATE) (Sseguya et al., 2021). The IPWRA has a comparative advantage over Propensity Score Matching (PSM) because it produces efficient estimates whenever it models the outcome and treatment equations and only allows one of the models to be rightly specified to estimate the average treatment effect (Sseguya et al., 2021). Unlike the PSM, which might have biased estimates whenever the propensity score model is incorrectly specified (Wooldridge, 2007). To get the average treatment effect, the IPWRA estimator combines the treatment model (inverse probability weighting) and the outcome model (regression adjustment).

Results and discussion

Impact of social protection on households' energy burdens

Table 2 presents Girinka and VUP social protection schemes' estimates of rural household energy burdens. The study regressed energy burden outcome on social protection scheme variables and other exogenous variables under ordinary least square regression (OLS) and the Lewbel Instrumental variable estimator. Since the social protection variable may be endogenous with the energy burden outcome variable, the social protection variable was instrumented internally following the Lewbel estimator (Baum & Lewbel, 2019b; Lewbel, 2018; Saroj, 2021). It was hard to get a valid external instrument in the available dataset. As such, Lewbel's Instrumental Variable Estimator is increasingly used in empirical economics to address this challenge (Elsas, 2021).

Overall, the study findings revealed that both Girinka and VUP social protection schemes significantly negatively affect rural energy burdens (dependent variable for all models), as shown in Table 2. This finding is contrary to the results of Nawaz and Iqbal (2020), who found that the Benazir Income Support Program (unconditional cash transfers) increased the share of fuel expenses in total household expenses in Pakistan. In simple terms, this paper found that the two social protection schemes decreased the proportion of fuel expenses in total household expenses as details follow. First, in column 1 under Table 2, we

Table 2
Estimates of the effects of social protection schemes (VUP & Girinka) on energy burden.

Variable	OLS (1)	IV (2)	OLS (3)	IV (4)
Access to VUP -bene	−0.237*** (0.089)	−0.188 (0.209)		
Access to Girinka (one cow, one family)			−0.356*** (0.109)	−0.297*** (0.136)
Gender (1 = male head)	0.252*** (0.078)	0.152 (0.107)	0.258*** (0.078)	0.156 (0.106)
Poor	−0.664*** (0.066)	−0.729*** (0.076)	−0.670*** (0.066)	−0.735*** (0.076)
Age of household head	−0.013 .*** (0.002)	−0.017*** (0.003)	−0.014*** (0.002)	−0.017*** (0.003)
The household head has no formal education		Ref.	Ref.	Ref.
The household head has primary education	0.146** (0.072)	0.117 (0.077)	0.143** (0.072)	0.115 (0.077)
The household head has secondary education	1.170*** (0.147)	1.221*** (0.250)	1.169*** (0.147)	1.222*** (0.251)
The household head has tertiary education	0.880*** (0.273)	0.652** (0.331)	0.864*** (0.273)	0.638** (0.331)
Tenancy-rented house	1.851*** (0.120)	2.081*** (0.250)	1.837*** (0.121)	2.069*** (0.250)
One room-house	−0.108 (0.083)	−0.094 (0.119)	−0.117 (0.083)	−0.102 (0.119)
Household size	−0.076*** (0.018)	−0.069*** (0.021)	−0.071*** (0.018)	−0.064*** (0.021)
The household head has a disability	−0.038 (0.130)	−0.108 (0.132)	−0.048 (0.130)	−0.117 (0.130)
Share of "able-bodied" adults (16–64 years)	−0.414 (0.268)	−0.407 (0.273)	−0.373 (0.268)	−0.374 (0.274)
Share of dependents (<16 years & >65 years)	0.210 (0.269)	0.260 (0.273)	(0.221) (0.269)	0.269 (0.274)
Kigali Province	4.192*** (0.179)	4.822*** (0.513)	4.182*** (0.179)	4.811*** (0.513)
Southern Province	−0.228*** (0.081)	−0.196*** (0.074)	−0.250*** (0.081)	−0.214*** (0.074)
Western Province	0.472*** (0.085)	0.514*** (0.092)	0.445*** (0.085)	0.491*** (0.091)
Northern Province	−0.127 (0.092)	−0.088 (0.082)	−0.141 (0.092)	−0.099 (0.082)
Eastern Province	Ref.	Ref.	Ref.	Ref.
Constant	2.648*** (0.311)	2.839*** (0.333)	2.651*** (0.310)	2.840*** (0.334)
K-P F-Statistic		50.577		56.186
Hansen J		24.538		26.753
Prob > χ^2		0.056		0.030

Standard errors in brackets; Statistical level of significance for the p-values: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

highlighted the OLS findings, while Column 2 highlighted the estimates of the Instrumental variable outcomes for the VUP social protection program. The study did not investigate the effect of the specific components of the VUP program but instead just assessed the overall impact of the VUP program on the energy burden. The OLS findings in Column 1 showed that access to the VUP program reduced the energy burden by 23.7 percentage points at a 1 % level of statistical significance. However, the results of the Lewbel estimator showed that access to VUP social protection reduced the energy burden by 18.8 percentage points. However, the Hansen J statistic revealed the problem of identification of the instruments as it was found to be significant at a 10 % level of statistical significance.

On the other hand, the OLS findings in Column 3 indicated that the Girinka program reduced energy burdens by 35.6 percentage points at a 1 % level of statistical significance. The results from the Lewbel Instrumental Variable estimator showed that the Girinka asset transfer program reduced energy burden by 29.7 percentage points, as reported in Column 4. The Hansen J statistic is also significant, implying that Girinka might be endogenous with the energy burden as the dependent variable. Since the Hansen J statistics are significant under the Lewbel estimator, this means issues of endogeneity and identification challenges on instruments for the two social protection programs such that results from the OLS regression models might yield inconsistent estimates. We also investigated further by coarsening the datasets first and applied the matching algorithms (Blackwell et al., 2009) to check the robustness of the results from the OLS regression (Nilsson et al., 2019) and the Lewbel Instrumental Variable Estimator in the following subsection. The pretreatment variables used for the coarsening dataset for Girinka social protection scheme included poverty status, location, number of cows, and access to pasture following Nilsson et al. (2019). On the other hand, to coarsen the dataset for VUP social protection scheme, we included poverty status, the share of disabled household members, the number of the elderly in the household, and Tropical livestock units (TLU) based on the literature on determinants of VUP participation in Rwanda (Gatzinsi et al., 2019; Habimana et al., 2021; Kidd & Kabare, 2019).

Robustness checking of the results

To check the robustness of the results, the analytical approach involved three stages. First, following Blackwell et al. (2009), Iacus et al. (2012), Lewbel (2018) and Nilsson et al. (2019), CEM was used to coarsen the dataset sets using some of the pretreatment variables (see Table A1 in the appendix), which were highlighted in the study by Nilsson et al. (2019) for Girinka social protection scheme. As for the VUP program, the pretreatment variables (see Table A2 in the appendix) were selected based on studies by Gatzinsi et al. (2019) and Habimana et al. (2021). Coarsening the data was necessary because a previous study in Rwanda revealed different factors that influence why some households fail to access the VUP social protection schemes (Gatzinsi et al., 2019). Secondly, using the output from CEM, the causal effect was estimated using the regression command by adding the CEM_weights and other control variables, and the results are presented in Table 3 (Blackwell et al., 2009).

The estimates (Table 3) from regression analysis using CEM_weights differ in magnitude from those of regression estimates using OLS and Lewbel Instrumental Variable approach (Table 2). Still, they had also shown significant negative effects. Specifically, the results showed that participation in the Girinka social protection programs translates into a substantial reduction in energy cost burden by 23.4 percentage points, as shown in column 2 in Table 3. On the other hand, participation in the VUP program may decrease the energy cost burden by 20.7 percentage points, as shown in column 4 in Table 3.

Thirdly, results from matching algorithms such as the nearest neighbor matching technique and others were employed to assess the impact of social protection schemes' access on household energy burden, and results are presented in Table 4. Participation in the Girinka program decreased the energy cost burden by 33.0 percentage points from inverse probability weighting regression adjustment (row 3 and column 2 in Table 4) and 32.4 percentage points under inverse probability weighting (row 4 and column 2 in Table 4). On the other hand, participation in the VUP program decreased the energy cost burden by 39.8 percentage points from inverse probability weighting regression adjustment (row 3 and Column 3 in Table 4) and 38.7 percentage points under inverse probability weighting (row 4 and Column 3 in Table 4).

Furthermore, the results from nearest-neighbor matching indicated that household involvement in the Girinka program led to a 30.5 percentage points decrease in the energy cost burden (row 5 and column 2

Table 3
Estimates of the effects of Girinka and VUP social protection schemes on energy burden with CEM weights.

Variable	Access to Girinka (one cow, one family)		Access to the VUP program	
	OLS (5)	OLS with CEM weights (6)	OLS (7)	OLS with CEM weights (8)
Access to Girinka (one cow, one family)	−0.249** (0.098)	−0.234*** (0.096)		
Access to the VUP program			−0.238*** (0.096)	−0.207** (0.0885)
Male headed household	0.247*** (0.086)	0.219*** (0.083)	0.275*** (0.081)	0.288*** (0.073)
Ubudu1	0.076 (0.175)	−0.023*** (0.166)	−0.163 (0.144)	−0.017 (0.142)
Ubudu2	0.130 (0.162)	0.034 (0.154)	−0.034 (0.129)	0.073 (0.132)
Ubudu3	0.309* (0.161)	0.269* (0.153)	0.208 (0.129)	0.317** (0.132)
Age of household head	−0.006** (0.002)	−0.004* (0.003)	−0.011*** (0.002)	−0.010*** (0.002)
The household head has primary education	0.171** (0.076)	0.208*** (0.074)	0.205*** (0.074)	0.203*** (0.067)
The household head has secondary education	1.164*** (0.165)	1.191*** (0.164)	1.387*** (0.151)	1.316*** (0.1613)
The household head has tertiary education	1.618*** (0.349)	1.976*** (0.361)	1.017*** (0.282)	1.344*** (0.332)
Tenancy-rented house	1.342*** (0.191)	2.159*** (0.125)	2.141*** (0.124)	1.760*** (0.133)
One room-house	−0.162 (0.099)	−0.178** (0.086)	−0.182** (0.086)	−0.307*** (0.083)
Household size	−0.092*** (0.019)	−0.127*** (0.018)	−0.130*** (0.018)	−0.149*** (0.017)
The household head has a disability	−0.043 (0.140)	−0.067 (0.134)	−0.059 (0.136)	−0.007 (0.098)
Share of “able-bodied” adults (16–64 years)	−0.559* (0.301)	−0.289 (0.276)	−0.290 (0.278)	0.114 (0.193)
Share of dependents (<16 years & >65 years)	0.118 (0.303)	0.142 (0.278)	0.167 (0.279)	0.555*** (0.204)
Constant	2.039*** (0.364)	2.504*** (0.331)	2.512*** (0.333)	2.043*** (0.275)
Observations	8173	8173	11,891	11,891

Standard errors in brackets; Statistical level of significance for the p-values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Effect of Girinka social protection scheme on energy burden.

Matching algorithm/Quasi-experimental technique	Household energy burden	
	ATE (Girinka scheme)	ATE (VUP program)
Inverse probability weighted regression adjustment (IPWRA)	−0.330*** (0.082)	−0.398*** (0.113)
Inverse Probability weights (IPW)	−0.324*** (0.084)	−0.387*** (0.126)
Nearest neighbor matching	−0.305*** (0.120)	−0.262** (0.133)
Number of observations		11,891

Standard errors in brackets; Statistical level of significance for the p-values: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

in Table 4). On the other hand, household participation in the VUP Program led to 26.2 percentage points in the energy cost burden (row 5 and column 3 in Table 4). The differences in the magnitude of the matching algorithm are attributed to the fact that the algorithm fails to handle endogeneity and heterogeneity that may come from unseen factors between the two groups, as is well expounded in the literature (Shiferaw et al., 2014). Nevertheless, the robustness results testing shows that all the methods revealed that the coefficients of the social protection variables on the energy cost burden were significantly negative at a 1 % level of statistical significance.

Conclusion and policy recommendations

This paper examined the effect of two social protection schemes (Girinka, Vision 2020 Umurenge) on household energy burdens in rural Rwanda by using the latest household-level microdata (EICV5). Rwanda is one of the African countries that institutionalized social protection programs to address food security and general poverty in its citizenry. Worth noting are visible complementary efforts from non-governmental organizations aimed at improving household well-being and inducing spillover effects at the grassroots level, particularly for poor communities. Furthermore, Rwanda also adopted a green growth development strategy to accelerate the uptake of renewable technologies over the recent years. As such, it offers a classic and favourable setting for the micro-econometric analyses that are key to bridging the research gap in the energy burden literature on the role played by social protection programs from a developing country context.

The Lewbel Instrumental Variable Estimator estimates, which account for the endogeneity problem and other quasi-experimental techniques (i.e., nearest neighbor matching, IPWRA, IPW), revealed that Girinka and VUP social protection schemes significantly negatively affected household energy cost burdens. The current study findings suggest that rural households might have prioritized other socio-economic needs, such as food or health, instead of energy, which may affect the overall household welfare. This finding is not consistent with those of Nawaz and Iqbal (2020), who found that the Benazir Income Support Program increased the share of fuel expenses in total household expenses among poor households in Pakistan. The study findings have policy implications regarding which rural families can afford and regularly use modern commercial energy services. Quantifying expenditures on different types of energy at varying accessibility of social protection schemes gives insight into the debate on the impact of energy burden on the rural poor amidst the higher energy prices during this post-Covid 19 era. Previous studies looked at how changes in energy prices may affect household welfare directly by comparing shares of expenditures on energy at different income levels in Africa and Asia (Bacon et al., 2010). In some cases, households do not entirely abandon traditional fuels because of various reasons ranging from cost, availability and reliability of modern fuel supplies and other social-cultural differences, which are not captured by the Integrated Living standards household surveys (Bacon et al., 2010).

Policy recommendations

These findings imply that much work is required and suggest the need to call for both a multisectoral approach and a multilayered level of support towards social protection projects design, implementation and upscaling to realize much better outcomes under sustainable goal number 7. First, the paper proposes a need to redesign the existing social protection schemes by making them becoming conditional programs to target energy poverty alleviation. For instance, the beneficiary households may receive energy safety nets to get solar home systems or solar panels at a subsidized rate depending on the capacity of the rural family under the "Theory of change" framework. In other cases, the beneficiary households can be organized to access off-grid energy solutions or renewable energy technologies such as solar via a cooperative arrangement. Secondly, the Rwandan government may consider engaging energy policy entrepreneurs at all levels as focal points in the energy policy process. This approach helps evaluate and explain energy poverty issues in rural areas using a holistic approach because several factors may interplay. Already Rwanda has multinational companies such as Mobisol and local organizations (i.e., sustainable village foundation) that are working on energy projects that can work hand in hand with the energy policy entrepreneurs at the provincial/district/local level. In so doing, these schemes will be transformed into convenient program for accelerating the uptake and use of clean energy.

Limitations of the study

The study did not look at the individual subcomponents of the VUP program, which consists of three pillars (Public works, direct support and financial services) due to the low numbers of the sampled households. In addition, it was difficult to assess the heterogeneity aspect of the treatment as livelihood interventions because the survey did not capture the duration (short period versus long period) in which the household has received the VUP support or the Girinka support. Future research should also investigate the combined effects of social protection schemes and other informal social protection schemes on energy burden, mainly looking at the urban areas where there are other formal social protection schemes (i.e., Rwandan Social Security scheme), which may not be available in the rural areas. Further studies are encouraged to look at these aspects using panel data for accounting for unobserved heterogeneity (time-invariant behavioral differences between individuals) in the modelling behavior, which this study could not explore further due to data limitations.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data. The data can be accessed upon special request from the National Institute of Statistics of Rwanda (http://www.statistics.gov.rw).

Appendix A

Table A1
Cem poor province cow pasture access, treatment (pubCow).

Matching summary:							
Number of strata: 63							
Number of matched strata: 24							
	0			1			
All	11,004			1002			
Matched	7171			1002			
Unmatched	3833			0			
Multivariate L1 distance: 0.51188894							
Univariate imbalance:							
	L1	Mean	Min	25 %	50 %	75 %	Max
Poor	4.3e−14	1.6e−14	0	0	0	0	0
Province	1.8e−14	1.7e−13	0	0	0	0	0
Cow	0.49897	0.55765	0	1	1	0	0
Pastureaccess	1.1e−15	6.7e−16	0	0	0	0	0

Table A2
Cem Shdisabled poor elderly TLU, treatment (VUPbene).

Matching summary:							
Number of strata: 108							
Number of matched strata: 52							
		0			1		
All		10,336			1670		
Matched		10,230			1661		
Unmatched		106			9		
Multivariate L1 distance: 0.21745202							
Univariate imbalance:							
	L1	Mean	Min	25 %	50 %	75 %	Max
Shdisabled	0.00838	0.0002	0	0	0	0	0
Poor	4.5e−14	3.1e−14	0	0	0	0	0
Elderly	2.4e−14	3.2e−14	0	0	0	0	0
TLU	0.0796	−0.02137	0	0	0.02	−0.04	−0.4

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