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## Article

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# Mobile money and multidimensional energy poverty: a cross-national study of Burkina Faso and Togo

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## ABSTRACT

Using data from the FinScop survey (2016), this study aims to analyse the effect of mobile money on multidimensional energy poverty (MEPI) in Burkina Faso and Togo. MEPI was calculated using the method of Alkire and Foster in 2011, and a linear regression based on the instrumental variable strategy was applied to control for endogeneity bias arising from the dual causality between energy poverty and mobile money. To test the robustness of our results, we used the endogenous switching regression (ESR) model to resolve the problems of self-selection bias and endogeneity. The average effects of treatment on the treated (ATT) and the untreated (ATU) were calculated from the coefficients of the ESR models. The incidence of multidimensional energy poverty was estimated at 90.7 and 91.1% in Burkina Faso and Togo, respectively. In addition, we found substantial differences between the subgroups in terms of multidimensional energy poverty in each of the countries. The results also robustly indicate that an increase in mobile money adoption per standard deviation is associated with a reduction in multidimensional energy poverty of  $-0.402$  standard deviations in the case of Burkina Faso and  $-0.628$  standard deviations in the case of Togo. We argue that mobile money can be an effective policy tool in the fight against energy poverty in developing countries.

## IMPACT STATEMENT

This research explores the impact of mobile money on multidimensional household fuel poverty by focusing on two developing countries (Burkina Faso and Togo). The comparative study between these two countries aims to shed light on the mechanisms by which mobile money influences household energy poverty. By analysing the effects of mobile money in different contexts, the study seeks to establish whether the results observed can be generalised. If the impact is similar in the two countries despite their differences, this would allow the conclusions to be applied on a more global level. The results highlight the need to integrate mobile money into policies aimed at reducing household energy poverty in developing countries.

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## 1. Introduction

Access to reliable, sustainable and modern energy services at an affordable cost is essential for socioeconomic development (Koomson & Danquah, 2021; Nussbaumer et al., 2012). It helps to reduce poverty by enabling other activities that are vital for human development (Birol, 2007; Bridge et al., 2016). Indeed, this access facilitates the use of certain technologies that are likely to reduce poverty through the channels of education, labour productivity and health (Bridge et al., 2016; Sambodo & Novandra, 2019). Also, the use of clean energy ensures a decent life for households because of its usefulness for cooking, lighting and commercial activities (Phoumin & Kimura, 2019; Reilly, 2015).

However, in Sub-Saharan Africa (SSA), almost 53% of the population has no access to electricity, and almost 85% of the population relies on inefficient cooking systems (International Energy Agency (IEA)

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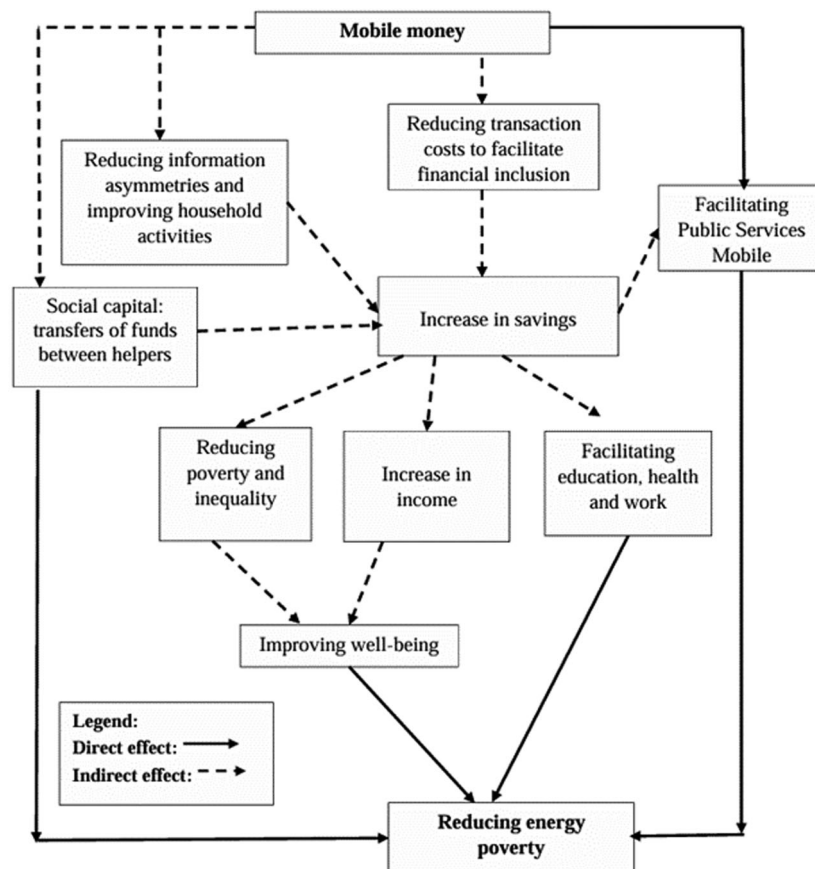
et al., 2020). People's reliance on inadequate energy services is a form of poverty as it limits their ability to meet their energy needs and realise their full potential (Practical Action, 2014). Energy poverty is defined as "the lack of sufficient choice to access affordable, reliable, high quality, secure, and environmentally sound energy services to support economic and human development" (Reddy et al., 2010). Limited access to clean fuels (electricity and gas) and their affordability are two factors that contribute to this energy poverty (Hosan et al., 2023).

Low household access to modern energy services can be explained by low purchasing power (Koomson & Danquah, 2021). Indeed, financial inaccessibility can force a person to modify their energy consumption in terms of quantity; this affects their standard of living, putting them in a situation of energy poverty (Lewis, 1982). Access to financial services can serve as a catalyst for improving household living conditions by enhancing their financial autonomy in the face of potential shocks (Afawubo et al., 2020; Duflo, 2020; Zhang & Posso, 2019). Previous studies have shown that financial inclusion plays a crucial role in poverty reduction and household well-being in general (Bukari & Koomson, 2020; Dabla-Norris et al., 2021; Koomson et al., 2020). Koomson and Danquah (2021) show that financial inclusion positively affects energy poverty reduction. These earlier studies focused on formal financial inclusion. Given that in developing countries, a large part of the population is excluded from using formal financial services (Apeti, 2022) it is appropriate to explore other alternatives that could help in alleviating energy poverty in these countries. In this regard, the development of mobile telephones can provide an alternative by allowing poor households to access basic financial services via mobile money (Apeti, 2022).

Advances in new technologies have facilitated the removal of certain barriers to accessing financial services through mobile money. These services via mobile phones promote the financial inclusion of vulnerable groups by reducing transaction costs (Bachas et al., 2018), access distances to financial services (Ahmad et al., 2020) and information asymmetries (Ahmad et al., 2020; Aron, 2018). Mobile money can also reduce poverty by transferring funds to the poor. It lowers transaction costs, and access to mobile money improves household welfare through economic security, increasing consumer spending (Haushofer & Shapiro, 2016; Hjelm et al., 2017; Munyegera & Matsumoto, 2016). Furthermore, it aids poverty reduction by improving household resilience to shocks. Mobile money increases people's propensity to save and, therefore, provides easy and rapid access to financial resources, especially for the most disadvantaged, thereby improving their ability to deal with health emergencies and react to negative shocks (Afawubo et al., 2020; Ky et al., 2018). Hence, access to financial services via mobile money is an effective approach to financially alleviating poverty, including that of vulnerable people (Álvarez-Gamboa et al., 2021; Koomson et al., 2020; Polloni-Silva et al., 2021).

The literature indicates that financial inclusion affects energy poverty through other transmission channels (Figure 1). According to Koomson and Danquah (2021), financial inclusion affects fuel poverty through its ability to increase household income and reduce monetary poverty and inequality, on the one hand, and through its investment effects in education, health and employment on the other. Zang et al. (2023) argue that the key factors determining fuel poverty are the price of energy, household income, access to energy appliances, a household's specific energy needs, lower levels of education and geographical barriers. Wachtel (2001) identifies the promotion of higher savings rates, through the provision of attractive and innovative products to encourage savings mobilisation, as one of the channels through which financial development influences a country's economic development.

In addition, the use of mobile telephones affects energy poverty in economic and social terms (Zang et al., 2023). From an economic perspective, the use of telephones can reduce the problems of information asymmetries in a households' activities, while improving their bargaining power and hence their profitability, which improves their well-being (Jensen, 2007; Quandt et al., 2020). Moreover, it can enhance family well-being through increased consumption (Labonne & Chase, 2009). Oezcan et al. (2013) found that overall family well-being had a significant impact on energy choice. On a social level, the use of mobile phones diminishes fuel poverty by influencing households' social capital. Indeed, the use of the mobile phone as a means of acquiring and exchanging information also affects trust with close friends, family or strangers in the social circle (Kushlev & Proulx, 2016). While Churchill and Smyth (2020) argue that trust stimulates the dissemination of effective information over social networks and that social trust is closely related to income poverty, productivity and the provision of public goods, opportunities in the labour market all play an important role in determining the degree of fuel poverty.



**Figure 1.** Mobile money transmission mechanism for reducing energy poverty.

Sources: authors based on literature review.

Therefore, the use of mobile phones can affect social capital, which plays a mediating role in the impact of mobile phone use on fuel poverty (Zang et al., 2023).

Empirical studies indicate that mobile money has a positive impact on the probability of saving in mobile money savings accounts and receiving remittances on the consumption expenditure, on the poverty reduction and the household (Churchill & Marisetty, 2019; Djahini-Afawoubo et al., 2023; Islam et al., 2022; Naito et al., 2021; Suri & Jack, 2016). As for the empirical literature on the effect of mobile money on energy poverty, it remains little explored. Nevertheless, Zang et al. (2023) show that mobile phone use has a positive impact on reducing energy poverty in Tibet and China. According to these authors, mobile telephones reduces energy poverty by increasing household income or by increasing their social capital. Koomson and Danquah (2021) find that an increase in financial inclusion is associated with a reduction in household energy poverty in Ghana. Similar findings were reported by Dogan et al. (2021) in Turkey, Wang et al. (2023) in China and Sen et al. (2023) in Bangladesh. However, an analysis of these studies reveals that they have not explicitly examined the effects of mobile money alone on energy poverty. Furthermore, its effect on multidimensional energy poverty has not been sufficiently explored in developing countries.

Given the findings that financial inclusion improves household welfare through its ability to mobilise savings to increase income, reduce poverty, and inequality, and thereby facilitate investment in education, health and family businesses, as well as efficiency gains, it is imperative to analyse the relationship between financial institutions and energy poverty. Therefore, this article aims to assess the capacity of financial inclusion through mobile money to reduce multidimensional household energy poverty in developing countries. This research contributes to the literature in three ways.

Firstly, it departs from previous studies examining the relationship between financial inclusion and fuel poverty, specifically examining the relationship between mobile money and multidimensional fuel poverty and providing strong evidence for two developing countries with high rates of multidimensional fuel poverty. In addition, the study takes a multidimensional approach to analysing the link between

mobile money and energy poverty. Energy poverty is a complex issue that lacks a consistent definition and is often difficult to quantify (Hosan et al., 2023). Furthermore, in developing countries, household energy poverty may involve simultaneous deprivations in terms of availability and affordability. It is, therefore, essential to measure energy poverty using a composite indicator that captures simultaneous affordability and availability deprivations (Crentsil et al., 2019; Hosan et al., 2023), which can be used to monitor progress towards the Sustainable Development Goals (Goal 7). This study is particularly important for developing countries, as it will help policymakers to formulate appropriate policies to reduce household dependence on traditional and polluting energy services.

Secondly, the article takes into account the risk of endogeneity associated with selection bias and the dual causality between mobile money and fuel poverty. In this case, the variable of interest, mobile money take-up, may be endogenous (Wooldridge, 2002). To resolve the problems of endogeneity and selection bias, two methods are used: the instrumental variable strategy and the endogenous switching regression model. Indeed, Nan et al. (2021) pointed out that the majority of studies on the socio-economic effects of mobile money have not used rigorous methodologies. Therefore, they suggested that future research should adopt more rigorous techniques, such as the instrumental variable technique, to control for endogeneity bias in order to obtain more robust results, and such a suggestion is considered within the scope of this article.

Using data from the FinScop survey (2016) conducted in Burkina Faso and Togo, this study aims to contribute to the growing literature on the determinants of energy poverty in developing countries. It is one of the few studies that examines the link between mobile money and energy poverty by providing robust evidence for two developing countries. In addition, the analysis is conducted as a comparative study between the two countries to provide insight into the mechanisms by which mobile money affects household fuel poverty. This comparative approach enhances our understanding of the causal relationship between mobile money and household well-being. Therefore, if the study reveals that the effect of mobile money on energy poverty reduction is similar in both countries, despite their differences, it suggests that the conclusions drawn can be applied globally. However, if disparities are observed, they would need to be applied on a case-by-case basis.

This article aims to analyse the effect of mobile money on energy poverty in Burkina Faso and Togo using a multidimensional measure of energy. The study covers a Sahelian country and a coastal country, i.e. Burkina Faso and Togo, respectively. Although the level of access to electricity remains a matter of some concern in these two countries, part of Burkina Faso's electricity demand is met by imports from Togo. Approximately 86% of households in Burkina Faso and 49% of households in Togo do not have access to electricity (International Energy Agency (IEA) et al., 2020<sup>1</sup>). For most households with access to electricity, reliability of supply and affordability remain significant concerns. Additionally, we note that almost 90% of households in Burkina Faso and almost 91% of households in Togo do not have access to clean cooking fuels and technologies (International Energy Agency (IEA) et al., 2020). This shows that firewood and charcoal are the main cooking fuels for 91.8% of these households in Burkina Faso and 49.3% in Togo (INSD, 2021;<sup>2</sup> INSEED, 2020)<sup>3</sup>. Indeed, fuel availability, lack of clean energy sources and their availability are the main reasons for the high use of solid fuels in developing countries (Khanna et al., 2019). Moreover, bank penetration rates are low in these countries, at 20.6% in Burkina Faso and 27% in Togo, according to the BCEAO<sup>4</sup> (BCEAO, 2021). However, with the emergence of mobile money services, the rate of use of financial services is increasingly compensated, leading to rates of 70.9% in Burkina Faso and 72.2% in Togo. In this context, mobile money is likely to assist households to meet their basic energy needs in these two countries, thereby helping to reduce energy poverty and improve social welfare. Consequently, this study aims to investigate the impact of mobile money on household energy poverty in these countries where financial inclusion is strongly enhanced by mobile phones. Given that mobile money has an impact on a household's ability to mobilise savings, it may have an impact on fuel poverty. Moreover, energy poverty can have a considerable impact on a household's well-being since energy is an integral part of daily life (Hosan et al., 2023).

The rest of the study is organised as follows. Section 3 presents various measures of fuel poverty, mobile money transmission channels and the relationship between mobile money and fuel poverty, while Section 4 presents the methodology, and describes the data and variables used. Section 5 analyses and discusses the results, and the final section presents the conclusion and policy implications.



## 2. Literature review

### 2.1. *Measuring energy poverty*

In the literature, no clear and universal definition of energy poverty exists (Sadath & Acharya, 2017). According to these authors, domestic energy deprivation, whether due to a lack of heating fuel in developed countries or a lack of access to electricity in developing countries, signifies energy poverty and has similar socio-economic consequences on society's well-being. However, Lewis (1982) defined energy poverty in terms of financial inaccessibility, whereby inadequate energy usage results from low-income levels, impacting people's standard of living. Regarding income, Leach (1992) showed that the ratio of energy consumption to household income is higher in low-income households than in middle-income households. This led to the introduction of the 10% income threshold by Boardman (1991). Based on this threshold, a person whose energy consumption exceeds 10% of their income is classified as experiencing energy poverty.

These definitions of energy poverty are mainly linked to affordability issues, whereas the situation appears to be more complex in developing countries. Energy poverty is perceived as a single-dimensional issue, primarily linked to income, in developed countries. However, in the analysis of the relationship between energy poverty and poverty, there are other important factors than income, such as the price or cost of energy in the assessment of energy poverty (Barnes et al., 2011; Hills, 2012).

This illustrates that energy poverty integrates multiple dimensions in the same logic as Amartya Sen's capability approach to development and goes beyond the income or expenditure incurred for energy consumption (Pereira et al., 2011; Sadath & Acharya, 2017). In this context, energy poverty represents an inability to realise essential capabilities due to insufficient access to affordable, reliable and secure energy services, considering alternative means to attain these capabilities in a reasonable manner (Day et al., 2016). In addition, households cannot adequately heat their homes or meet other essential domestic energy services at affordable costs (Pye et al., 2015). Access to clean, modern, and affordable energy is recognised as facilitating the attainment of several Sustainable Development Goals (SDGs), including Poverty eradication (SDG1), Hunger eradication (SDG2), Good health and well-being (SDG3), Quality education (SDG4), Gender equality (SDG5), Decent work and economic growth (SDG8), Industry, innovation, and infrastructure (SDG9) and Sustainable cities and communities (SDG11), as outlined by Sambodo and Novandra (2019).

Thus, recent studies have considered energy poverty from a multidimensional perspective (Day et al., 2016; Ogwumike & Ozughalu, 2016; Sadath & Acharya, 2017). Within this multidimensional framework, Nussbaumer et al. (2012) propose a multidimensional energy poverty index that considers factors such as energy access and other energy-related development considerations, including the type of cooking fuel and ownership of electrical appliances, e.g. refrigerators, radios, televisions and mobile phones. This research follows the same logic and uses this index for further analysis.

### 2.2. *Theoretical literature: mobile money transmission channels*

Access to clean, affordable, stable, sustainable and modern energy sources improves socio-economic development and enables the achievement of the Sustainable Development Goals (SDGs), poverty eradication, gender equality, zero hunger, climate action, good health, and well-being (Crentsil et al., 2019; Rosenthal et al., 2018). The literature distinguishes between two main channels by which financial inclusion through mobile money can reduce fuel poverty.

Mobile money contributes to the alleviation of energy poverty by reducing transaction costs and promoting financial inclusion across all segments of society (Aker et al., 2016; Álvarez-Gamboa et al., 2021; Koomson et al., 2020). Financial inclusion through mobile money improves household income and reduces inequality and poverty because it allows households to reduce economic shocks, maintain consumption levels over time and make future investments (Demirgüç-Kunt et al., 2017; Koomson & Danquah, 2021). To this end, Koomson et al. (2020) show that an increase in financial inclusion correlates with a decrease in a household's probability of poverty and inhibits its risk of poverty. In this case, it offers blocked development prospects for disadvantaged segments of the population and reduces income inequality (Omar & Inaba, 2020; Park & Mercado, 2018). Promoting equal opportunities to access

financial services fosters the economic integration of socially excluded households and maximises society's overall well-being (Nanziri, 2016; Sani Ibrahim et al., 2019). This means that an increase in inequality or poverty has increasing effects on fuel poverty, whereas an increase in income reduces fuel poverty (Bouzarovski & Petrova, 2015; Casillas & Kammen, 2010; Churchill & Smyth, 2020; Khandker et al., 2010; Sadath & Acharya, 2017). This underscores the potential of financial inclusion to influence fuel poverty by impacting household income, poverty levels and inequality.

Financial inclusion can also reduce energy poverty through its ability to mobilise savings (Afawubo et al., 2020; Ky et al., 2018) needed for improvements in education, health and work (Matekenya et al., 2020; Njiru & Letema, 2018; Sarma & Pais, 2011; Stein & Yannelis, 2019). These improvements can increase the likelihood of higher earned incomes and, thus, increase households' means of acquiring reliable, stable and sustainable energy sources for basic needs. Indeed, increasing the level of education reduces fuel poverty, although this effect is not significant in some studies (Crentsil et al., 2019; Sadath & Acharya, 2017; Sharma, 2016). Moreover, fuel poverty decreases as the education level of the household head increases (Crentsil et al., 2019). This implies that the level of energy poverty decreases for households with a high level of education. Financial inclusion makes it possible to earn income for immediate needs, such as health care, in order to maintain or improve the level of productivity in activities, which allows access to the necessary energy sources. Conversely, the absence of these energy sources can considerably worsen health problems (Biermann, 2016; Kahouli, 2020; Llorca et al., 2020). Based on the existing literature, the mobile money transmission mechanism that forms the theoretical framework for this study can be represented in Figure 1.

### 3. Methodology

#### 3.1. Measuring the multidimensional energy poverty index (MEPI)

For the measurement of MEPI, the study adopts the framework of Nussbaumer et al. (2012) derived from the literature on multidimensional poverty measures including the Oxford Poverty and Human Development Initiative (OPHI) developed by Alkire and Foster (2011). The MEPI assesses the sources and types of energy in which the households are poor. It involves the first stage of identifying energy-poor households based on the range of energy deprivations suffered by households, and a second stage that aggregates the information to reflect energy poverty in a holistic way. The unit of analysis for MEPI is the household. It is an index of four dimensions, each comprising an indicator representing access to, and use of, basic energy services (Table 1). Each indicator is coded 1 if the household is deprived of the indicator and 0 otherwise. An unequal weighting was assigned to each indicator according to its importance in measuring multidimensional energy poverty. Consequently, a multidimensional energy deprivation score is determined for each household by adding the weighted deprivations ( $c_i$ ) in such a way that the deprivation score is between 0 and 1.

The higher the deprivation experienced by the household, the higher the deprivation score. The maximum score was 1 if the individual suffered deprivation in all indicators. Formally we have:

$$c_i(k) = w_1 I_1 + w_2 I_2 + \dots w_d I_d \quad (1)$$

where  $c_i(k)$  represents the energy deprivation scores,  $I_i = 1$  if the household is deprived of indicator  $i$  and  $I_i = 0$  otherwise, and  $w_i$  is the weight associated with indicator  $i$  with  $\sum_{i=1}^d w_i = 1$ .

**Table 1.** Dimension, indicators, deprivation thresholds and weightings.

Dimensions/Indicators		Deprivation cut-offs	Weights
<i>Lighting</i>			
Electricity	The household has no electricity		0.3
<i>Cooking</i>			
Modern cooking fuel	The household cooks with biomass (firewood, cow dung, wood, charcoal)		0.3
<i>Services provided by means of a household appliance</i>			
Asset ownership	The household does not own a refrigerator or freezer		0.2
<i>Education and entertainment</i>			
Education and entertainment	The household does not own a radio or television		0.2

Source: Based on Nussbaumer et al. (2012).



These deprivation scores are subsequently compared by a predefined poverty line ( $k$ ) so that a household is considered multidimensionally poor if  $c_i \geq k$ . Following Nussbaumer et al. (2012), we define a household as multidimensionally energy-poor if its deprivation score is greater than, or equal to, 0.33 ( $k = 0.33$ ).

The MEPI represents the product of the incidence and intensity of multidimensional energy poverty. The incidence, which represents the proportion of people considered to be energy-poor, was calculated as follows:

$$H = \frac{q}{n} \quad (2)$$

where  $q$  is the number of multidimensionally energy-poor households and  $n$  is the total number of households.

Energy poverty intensity indicates the average proportion of indicators for which multi-dimensionally energy-poor households are deprived. Poverty intensity ( $A$ ) is the average deprivation score of households identified as energy-poor, and is obtained as follows:

$$A = \frac{\sum_{i=1}^n c_i(k)}{q} \quad (3)$$

The MEPI is obtained by multiplying the incidence and intensity of energy poverty:

$$MEPI = H \times A = \frac{\sum_{i=1}^n c_i(k)}{n}$$

The MEPI respects the condition of dimensional monotonicity. It can also be broken down into sub-groups (according to gender, place of residence, etc.).

### 3.2. Dimensions, indicators and thresholds of deprivation

The dimensions, indicators and deprivation thresholds, as well as the weights used in the MEPI estimation for Burkina Faso and Togo, are presented in Table 1. In this study, four dimensions and indicators were used to measure multidimensional energy poverty. The choice of these indicators and deprivation thresholds is a relevant reflection of the household energy demand services. The weights are applied unevenly to reflect the relative importance of multidimensional energy poverty (Nussbaumer et al., 2012).

### 3.3. Specification and empirical methods

According to the literature, the mobile money variable is considered to be potentially endogenous (Djahini-Afawoubo et al., 2023; Islam et al., 2022; Riley, 2018). The source of endogeneity may arise from the bidirectional causality inherent in the relationship between mobile money and multidimensional energy poverty. Indeed, we argue that mobile money can help to reduce household energy poverty. However, poor households seeking access to modern energy sources may choose to save via mobile money to achieve this (Koomson & Danquah, 2021). Thus, the decision to adopt mobile money may be influenced by the household's decision to access modern energy services. Furthermore, the decision to adopt mobile money may be correlated with observable, as well as unobservable, characteristics, thus introducing bias due to the heterogeneity of individuals in the sample. We use an instrumental variable method to deal with this endogeneity problem (Bezu et al., 2014; Djahini-Afawoubo et al., 2023; Verkaart et al., 2017).

This work uses a linear regression model with an instrumental variable (IV). The objective is to find an instrumental variable that is strongly correlated with moving money and uncorrelated with the error term in structural Eq. (1). Thus, we specify the model as follows:

$$AM_i^* = \delta + \beta Dist_i + \varepsilon_{i1} \quad (1)$$

$$EnPov_i = \alpha + AM_i^* + \gamma X_i + \varepsilon_{i2} \quad (2)$$

where  $EnPov_i$  is the dependent variable representing multidimensional energy poverty. It is measured using household energy deprivation scores (see Eq. 1).  $AM_i^*$  is the adoption of mobile money. It is a

binary variable that takes the value of 1 if the individual adopts mobile money, and 0 otherwise.  $X$  represents the other explanatory variables in the model.

Following previous studies (Afawubo et al., 2020; Djahini-Afawoubo et al., 2023), we use the time taken to reach a mobile money agent's branch as an instrument. This is a variable with six modalities: "Less than 10 minutes," "11–20 minutes", "21–30 minutes", "31–60 minutes", "61 minutes–2 hours" and "> 2 hours". Furthermore, the validity of an instrument relies on two main conditions: it must have a direct relationship with the potentially endogenous variable, but no direct relationship with the dependent variable (Cameron & Trivedi, 2010; Koomson et al., 2020). Our instrument, the time taken to get to the nearest mobile money agency, satisfies both conditions. Indeed, our instrument is directly linked to mobile money, as the closer the individual is to a mobile money agency, the lower the associated financial, in-kind and psychological costs, leading to rapid and/or frequent use of mobile money (Djahini-Afawoubo et al., 2023). However, the time it takes to visit a mobile money branch only affects energy poverty through its influence on mobile money.

In addition to the estimates from the instrumental variable strategy, we use the endogenous switching regression (ESR) model capable of handling selection bias and endogeneity problems (Ahmed & Mesfin, 2017; Asfaw et al., 2012; Di Falco et al., 2011; Nonvide, 2023) to ensure the robustness of the results. This method involves two stages. The first step of the ESR model specification concerns the definition of the selection equation.

The mobile money adoption selection equation is specified as follows:

$$AM_i^* = \delta X_i + \mu_i \text{ with } AM_i^* = \begin{cases} 1 & \text{if } AM_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where  $AM_i$  is a binary variable taking the value 1 for mobile money adoption and 0 otherwise;  $X_i$  is a vector of factors influencing mobile money adoption;  $\varphi_i$  is an error term assumed to be normally distributed with zero mean.

We adopt the endogenous switching regression model of multidimensional energy deprivation in which individuals are faced with two regimes (1) adopting mobile money and (2) not adopting mobile money, specified as follows:

$$\text{Regime 1: } EnPov_{1i} = \beta_1 Z_i + \varepsilon_{1i} \text{ if } AM_i = 1 \quad (4)$$

$$\text{Regime 2: } EnPov_{0i} = \beta_0 Z_i + \varepsilon_{0i} \text{ if } AM_i = 0 \quad (5)$$

where  $EnPov_i$  represents the multidimensional energy deprivation scores in regimes 1 and 2.  $Z_i$  represents a vector of exogenous variables assumed to explain multidimensional energy deprivation.  $\varepsilon_{ij}$  are the two error terms in the equation that are assumed to have a trivariate normal distribution, with mean 0 and non-singular covariance matrix (Did you mean matrix rather than martice?) (Ahmed & Mesfin, 2017; Lokshin & Sajaia, 2004) expressed as follows:

$$\text{cov}(\varepsilon_{1i}; \varepsilon_{2i}; \mu_i) = \begin{pmatrix} \sigma_{\varepsilon 1}^2 & \cdot & \sigma_{\varepsilon 1 \mu} \\ \cdot & \sigma_{\varepsilon 0}^2 & \sigma_{\varepsilon 0 \mu} \\ \cdot & \cdot & \sigma_{\mu}^2 \end{pmatrix} \quad (6)$$

where  $\sigma_{\mu}^2$  is the variance of the error term in the selection equation (Eq. (3)),  $\sigma_{\varepsilon 1}^2$  and  $\sigma_{\varepsilon 0}^2$  are the variances of the error terms in the outcome equations (Eqs. (4) and (5)).  $\sigma_{\varepsilon 1 \mu}$  and  $\sigma_{\varepsilon 0 \mu}$  represent the covariance of  $\mu_i \varepsilon_{1i}$  and  $\varepsilon_{0i}$ . The expected values of  $\varepsilon_{1i}$  and  $\varepsilon_{0i}$  conditional on sample selection are non-zero:

$$E[\varepsilon_{1i} | AM_i = 1] = \sigma_{\varepsilon 1 \mu} \frac{\phi(\beta x_i)}{\Phi(\beta x_i)} = \sigma_{\varepsilon 1 \mu} \lambda_{1i} \quad (7)$$

and

$$E[\varepsilon_{0i} | AM_i = 0] = \sigma_{\varepsilon 0 \mu} \frac{\phi(\beta x_i)}{1 - \Phi(\beta x_i)} = \sigma_{\varepsilon 0 \mu} \lambda_{0i} \quad (8)$$

where  $\phi(\cdot)$  is the standard normal probability density function,  $\Phi(\cdot)$  the standard normal cumulative density function, and  $\frac{\phi(\beta x_i)}{\Phi(\beta x_i)} = \lambda_{1i}$  and  $\frac{\phi(\beta x_i)}{1 - \Phi(\beta x_i)} = \lambda_{0i}$ .

In addition, the coefficients of the ESR model can be used to calculate the average treatment effect on treated individuals (ATT) and the average treatment effect on untreated individuals (ATU). The observed and unobserved counterfactual results for the multidimensional energy deprivation scores are presented below:

Adopters who have adopted mobile money:

$$E(EnPov_{1i}/AM_i = 1) = Z_{1i}\beta_1 + \sigma_{\varepsilon 1\mu}\lambda_{1i} \quad (9)$$

If the adopters had not adopted mobile money (counterfactual)

$$E(EnPov_{0i}/AM_i = 1) = Z_{1i}\beta_0 + \sigma_{\varepsilon 0\mu}\lambda_{1i} \quad (10)$$

Non-adopters without mobile money adoption:

$$E(EnPov_{0i}/AM_i = 0) = Z_{0i}\beta_0 + \sigma_{\varepsilon 0\mu}\lambda_{0i} \quad (11)$$

If non-adopters had adopted mobile money (counterfactual):

$$E(EnPov_{1i}/AM_i = 0) = Z_{0i}\beta_1 + \sigma_{\varepsilon 1\mu}\lambda_{0i} \quad (12)$$

Therefore, the mobile money adopter ATT is calculated as the difference between (9) and (10):

$$ATT = E(EnPov_{1i}/AM_i = 1) - E(EnPov_{0i}/AM_i = 1) = Z_{1i}(\beta_1 - \beta_0) + (\sigma_{\varepsilon 1\mu} - \sigma_{\varepsilon 0\mu})\lambda_{1i} \quad (13)$$

which represents the average effect of mobile money adoption on the multidimensional energy deprivation scores of those who have actually adopted mobile money.

Similarly, the ATU for non-adopters is calculated as the difference between (12) and (11):

$$ATU = E(EnPov_{1i}/AM_i = 0) - E(EnPov_{0i}/AM_i = 0) = Z_{0i}(\beta_1 - \beta_0) + (\sigma_{\varepsilon 1\mu} - \sigma_{\varepsilon 0\mu})\lambda_{0i} \quad (14)$$

which represents the average effect of the treatment on non-adopters if they had adopted mobile money.

### 3.4. The data

The data used in this research were obtained from the FinScope survey conducted in 2016 in Burkina Faso by the "Institut National de la Statistique et de la Démographie (INSD)" and in Togo by the "Institut National des Statistiques, des Etudes Economiques et Démographiques (INSEED)" in collaboration with the South African agency FinMark Trust. FinScop is a nationally representative survey of consumer behaviour and interaction with financial services, their experiences and perceptions of financial services, their demographic and geographic distributions, and their current levels of access to, and use of, financial services and products. The survey was carried out on a sample of 5066 adults (aged 15 and over) in Burkina Faso and 5197 people in Togo. Table 2 presents the variables used in the analyses.

**Table 2.** Presentation of variables.

Variable	Definition of variables used
Multidimensional energy poverty	Household energy deprivation scores
Age	Age in completed years
Age squared	Age in completed years squared
Female	=1 if female and 0 if male
Married	=1 if married and 0 otherwise
Literacy	=1 if literate and 0 otherwise
Household size	Number of persons in household
Household size squared	Number of persons in household squared
Urban	=1 if urban and 0 otherwise
Social capital	=1 if member of a social group and 0 otherwise
Self-employed	=1 if self-employed and 0 otherwise
Employed	=1 if employed and 0 otherwise

Source: authors.

## 4. Results

### 4.1. Deprivation and contribution of indicators to MEPI

Table 3 presents the levels of deprivation of the indicators based on the thresholds adopted, as well as the contributions of these indicators to multidimensional energy poverty in the two countries. We observe that deprivation of access to electricity is twice as high in Burkina Faso as in Togo. This scale of deprivation of access to electricity in Burkina Faso reflects an increase in the contribution of the access to electricity indicator to the MEPI in Burkina Faso compared to Togo. In Burkina Faso, access to electricity contributed 0.34% to the MEPI, whereas in Togo, the contribution was 0.194%.

Deprivation of the use of modern cooking fuels is very high in both countries; however, deprivation was relatively lower in Burkina Faso than in Togo. In Burkina Faso, 92.32% of households rely on solid biomass as their primary source of cooking fuel; by contrast, in Togo, almost 94% of households depend on such fuels. However, this high level of household dependence on solid biomass for cooking can lead to health problems caused by indoor air pollution (Gonzalez, 2016). In terms of contribution to the IPEM, the modern fuel use indicator contributed 0.36% to Burkina Faso and 0.43% to Togo. This makes modern cooking fuel deprivation the indicator that contributes the most to the MEPI in both countries.

Concerning deprivation linked to the use of fridges/freezers (asset holdings), it was 92.46% in Burkina Faso and 94.45% in Togo. In terms of contribution to the MEPI, it was 0.24% in Burkina Faso and 0.29% in Togo. Similarly, deprivation of education and entertainment (television or radio) accounted for 20.27% in Burkina Faso and 26.42% in Togo. This indicator contributed 0.06% to the MEPI for Burkina Faso and 0.08% for Togo.

### 4.2. Multidimensional energy poverty index (MEPI)

Table 4 presents the results of the estimates of the incidence, intensity and index of multidimensional energy poverty for the two countries. The results indicate a slight difference in the multidimensional energy poverty rate between the two countries. The incidence of multidimensional energy poverty was estimated to be 90.7% in Burkina Faso and 91.1% in Togo, a difference of 0.4%. The intensity of multidimensional energy poverty, which measures the weighted average deprivation of households with low energy consumption, was estimated at 0.816 in Burkina Faso and 0.690 in Togo. Thus, in Burkina Faso,

**Table 3.** Deprivation and contribution of indicators to MEPI, Burkina Faso and Togo.

Dimensions/Indicators	Deprived of indicator (%)		Contributions of indicator	
	Burkina Faso	Togo	Burkina Faso	Togo
<i>Lighting</i>				
Electricity	83.221	40.714	0.337	0.194
<i>Cooking</i>				
Modern cooking fuel	92.321	93.994	0.364	0.432
<i>Services provided by means of a household appliance</i>				
Asset ownership	92.46	94.450	0.244	0.289
<i>Education and entertainment</i>				
Education and entertainment	20.272	26.42	0.055	0.084

Source: Authors' computation.

**Table 4.** Estimate of MEPI Burkina Faso and Togo.

Estimates	Burkina Faso	Togo
Head count (H)	0.907*** (0.004)	0.911*** (0.004)
Additional (A)	0.816*** (0.002)	0.690*** (0.003)
MEPI (H × A)	0.74*** (0.004)	0.628*** (0.004)
Observations	5066	5045

Robust standard errors in parentheses were adjusted for the survey design.

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ .

Source: Authors' computation.

household's poor in multidimensional energy were deprived of almost 82% of the weighted indicators, while in Togo, these poor households were deprived of 69% of the weighted indicators. Given that the intensity of multidimensional energy poverty is higher in Burkina Faso than in Togo, and that the incidence of multidimensional energy poverty is almost similar in the two countries, the multidimensional energy poverty index is higher in Burkina Faso than in Togo. In fact, in Burkina Faso, it is estimated at 0.74, whereas it is estimated to be 0.628 in Togo.

### 4.3. Breakdown of MEPI into sub-groups

The breakdown of the MEPI by gender and area of residence is shown in Table 5. The results indicate substantial differences in the incidence and intensity of multidimensional energy poverty according to the gender and area of residence of the household head. Overall, multidimensional energy poverty is predominantly male-dominated. The incidence of multidimensional energy poverty in male-headed households is estimated at 91.9% in Burkina Faso and 91.8% in Togo. However, 80.9% of female-headed households are in multidimensional energy poverty in Burkina Faso, while 90.5% of female-headed households are in energy poverty in Togo. The intensity of multidimensional energy poverty is male-dominated in Burkina Faso and female-dominated in Togo. Furthermore, the results did not show a significant difference between male-headed and female-headed households in Burkina Faso. Indeed, male-headed households in multidimensional energy poverty were deprived of 81.16% of the indicators in Burkina Faso and 67.8% in Togo, whereas female-headed households were deprived of 81.12% of the indicators in Burkina Faso and 69.7% in Togo. The MEPI was higher for male-headed households in Burkina Faso and slightly higher for female-headed households in Togo. The MEPI for male-headed households in Burkina Faso and Togo were 0.749 and 0.622, respectively. Female-headed households in Burkina Faso and Togo were 0.657 and 0.631, respectively.

The results also indicated significant differences in the incidence and intensity of multidimensional energy poverty between rural and urban households in the two countries. The incidence and intensity of multidimensional energy poverty are more prevalent in rural areas than in urban ones. In fact, the incidence is estimated at 99.5% in rural areas in Burkina Faso, and 83.7% of the weighted indicators are deprived of multidimensional energy poverty. The MEPI index for rural households in Burkina Faso was 0.832. In Togo, the incidence and intensity of multidimensional energy poverty among rural households are lower than in Burkina Faso. The incidence of multidimensional energy poverty is estimated at 98.3%, while the average deprivation of rural households in multidimensional energy poverty is estimated at 79.3% in Togo. The MEPI for rural households in Togo is estimated to be 0.78.

In urban areas, 57.8% of households were in multidimensional energy poverty in Burkina Faso. These households were deprived of 68.3% of weighted indicators. Therefore, the MEPI for urban areas in Burkina Faso is estimated to be 0.395. In Togo, 86% of the households in urban areas were in a multidimensional energy poverty situation. These poor households were deprived of 60.7% of weighted indicators. The MEPI in Togo's urban areas was estimated to be 0.522.

**Table 5.** Sub-group decomposition of multidimensional energy poverty index.

Sex	Burkina Faso			Togo		
	H	A	MEPI	H	A	MEPI
Male	0.919*** (0.005)	0.816*** (0.002)	0.749*** (0.005)	0.918*** (0.006)	0.678*** (0.004)	0.622*** (0.006)
Female	0.809*** (0.037)	0.812*** (0.018)	0.657*** (0.005)	0.905*** (0.014)	0.697*** (0.010)	0.631*** (0.013)
<i>Residence type of household</i>						
Urban	0.578*** (0.015)	0.683*** (0.007)	0.395*** (0.011)	0.860*** (0.006)	0.607*** (0.003)	0.522*** (0.005)
Rural	0.995*** (0.001)	0.837*** (0.002)	0.832*** (0.002)	0.983*** (0.003)	0.793*** (0.004)	0.780*** (0.005)

Robust standard errors in parentheses were adjusted for the survey design.

\*\*\* $p < 0.01$ ; \*\* $p < 0.05$ ; \* $p < 0.1$ .

Source: Authors' computation.

#### 4.4. Sensitivity analysis

The MEPI measure can be vulnerable to the threshold set and the weights used. We carry out two different sensitivity analyses to test the robustness of the index.

To test the sensitivity with respect to the set threshold, we will proceed to a modification of the multidimensional energy poverty threshold  $k$  in order to evaluate its impact on the MEPI and on  $H$  (incidence of multidimensional energy poverty) for all subgroups (rural and urban) (Adusah-Poku & Takeuchi, 2019; Nussbaumer et al., 2012). Robustness is tested by changing the  $k$  threshold between 0.2 and 0.4. The results are presented in Tables A and B in Appendix. The results show that changing the multidimensional energy poverty threshold does not lead to any significant change in the values of MEPI and  $H$ . An important observation is that the values of MEPI and  $H$  decrease when the threshold is changed from 0.2 to 0.33.

For the sensitivity test against the weights, we use the rank sum method for assigning the different weights (Adusah-Poku & Takeuchi, 2019; Sadath & Acharya, 2017). In accordance with Adusah-Poku and Takeuchi (2019), before assigning the weights, we grouped the service dimension provided by means of a household appliance and the education/entertainment dimension into a single main dimension called 'additional measures'. In this way, the four dimensions have been reduced to three, which are ranked according to the relative importance of the individual dimensions. Weights are calculated using the following formula:

$$W_{ti} = \frac{K - ri + 1}{\sum_{j=1}^K K - ri + 1}$$

where  $ri$  is the rank of the  $i^{th}$  lens and  $K$  is the total number of lenses. Using the above formula, a weighting of 0.50; 0.33 and 0.17 is calculated for the kitchen, lighting and supplementary measures dimensions respectively. In line with Sadath and Acharya (2017) and Adusah-Poku and Takeuchi (2019), we adopt two ranking systems: the first, kitchen, lighting and supplementary measures, and the second, lighting, kitchen, and supplementary measures. The weight is divided equally if a dimension has more than one indicator. The results are presented in Tables C and D in Appendix. The results obtained indicate that changes in the weights of the dimensions do not also lead to significant changes in the values of the MEPI and  $H$  (incidence of energy poverty).

Based on the results of the sensitivity analysis, we can, therefore, say that the MEPI and the  $H$ -index are robust to the weightings and thresholds used in the construction of the index.

#### 4.5. Descriptive statistics of variables according to whether or not mobile banking is adopted

Table 6 presents the characteristics of the individuals used as variables in the subsequent models. The statistical results indicate a lower incidence of multidimensional energy poverty with the adoption of mobile money in both the countries. With the adoption of mobile money, the incidence of

**Table 6.** Descriptive statistics for the variables used.

Variable	Burkina Faso		Togo	
	Mobile money adopted	Mobile money not adopted	Mobile money adopted	Mobile money not adopted
Multidimensional energy poverty	0.577	0.818	0.542	0.684
Age	35.454	34.172	33.868	36.174
Age squared	1430.333	1399.440	1298.855	1585.086
Female	0.385	0.517	0.456	0.596
Married	0.644	0.634	0.600	0.578
Literacy	0.561	0.243	0.122	0.136
Household size	7.147	7.558	6.528	6.683
Household size squared	86.045	89.018	56.242	58.224
Urban	0.470	0.112	0.778	0.506
Social capital	0.167	0.190	0.632	0.472
Self-employed	0.481	0.539	0.157	0.126
Employed	0.057	0.002	0.107	0.028

Robust standard errors in parentheses adjusted for survey design.

Source: Authors' computation.



multidimensional energy poverty for Burkina Faso and Togo was 57.7 and 54.2%, respectively, whereas without the adoption of mobile money, the incidence was 81.1 and 68.4%, respectively. These statistical analyses suggest that the adoption of mobile money is likely to reduce household energy poverty in both countries.

The statistical results also indicated a low take-up of mobile money by women in both countries. In urban areas, mobile money users outnumber non-users in both the countries. In Burkina Faso, mobile money adoption is three times higher than non-adoption, whereas in Togo, it is almost twice as high. Self-employed workers in Burkina Faso have adopted more mobile money than those in Togo; however, it should be noted that workers who do not adopt mobile money are more numerous than those in Burkina Faso. This is not the case for Togo. Similarly, the adoption of mobile money by employees in Burkina Faso was lower than that in Togo. Employees who do not adopt mobile money are higher than those who do so in Burkina Faso and lower in Togo.

#### **4.6. Effect of adopting mobile money on multidimensional energy poverty**

Table 7 presents the estimates of the effect of mobile money adoption on multidimensional energy poverty. To account for the endogeneity problem, we estimate a 2SLS regression using our measure of distance to a mobile money agency. The Durbin and Wu-Hausman endogeneity tests indicate that mobile money variable is endogenous since the probability of rejecting the null hypothesis of exogeneity is below the 1% threshold, which justifies the use of the instrumental variable method to deal with endogeneity problems. Furthermore, on the basis of the validated instrumental variable tests carried out, we reject the weak instrument hypothesis (Table 7). Table 7 also presents the regression result of the first step with the instrument (time to reach the nearest mobile money agent). As expected, the coefficients of our instrument are negative and significant at 1%, indicating that an increase in distance to the nearest mobile money agent is associated with a decrease in mobile money adoption in both countries. F-test statistics on the null effect of the instrument reject this hypothesis. Furthermore, in accordance with Staiger and Stock (1997), the F-statistics are well above the threshold of 10, indicating that our instrument does not have a weak relationship with mobile money. The Anderson-Rubin Wald test and the Stock-Wright LM test also show that we can easily reject the null hypothesis that the endogenous regressor has no effect, indicating that our endogenous regressor is relevant. Based on these results, we conclude that our instrument does not suffer from statistical weakness. Moreover, the estimation results show that mobile money has a positive and significant effect on reducing multidimensional energy poverty in both countries. Additionally, age, age squared, gender, literacy, household size, household size squared, social capital, being employed and being self-employed have a statistically significant effect on multidimensional energy poverty.

#### **4.7. Discussion**

The estimation results show that mobile money adoption is associated with a decrease in multidimensional energy poverty in both the countries. An increase in mobile money adoption per standard deviation is associated with a reduction in multidimensional energy poverty of  $-0.402$  standard deviations in the case of Burkina Faso and  $-0.628$  standard deviations in the case of Togo. Therefore, we can deduce that mobile money can be a channel for households to mobilise the financial resources needed to access modern energy services. Weak purchasing power prevents households from accessing modern energy services (Adusah-Poku & Takeuchi, 2019; Koomson & Danquah, 2021). The use of mobile money helps to improve household purchasing power through the receipt of funds from migrants. It is clear that households that regularly benefit from these money transfers are more likely to access modern energy sources than those that do not. Munyegera and Matsumoto (2016) find in their studies that mobile money-users have a significantly higher probability of receiving remittances, and that remittances are more frequent and of higher value compared to those of non-users. Jack and Suri (2014) show that in Kenya, remittances received by households (through mobile money) have increased their incomes by 3% to 4%. In addition to increasing household income through remittances, by making payments easier

**Table 7.** Mobile money and energy poverty (2SLS regression).

Variables	Burkina Faso	Togo
Mobile money adoption	−0.2138*** (0.0162) [−0.4015]	−0.3373*** (0.0816) [−0.6275]
Age	−0.0030*** (0.0008) [−0.1819]	0.0015 (0.0015) [0.0966]
Age squared	0.0000*** (0.0000) [0.1811]	−0.0000 (0.0000) [−0.0807]
Sex (female)	−0.0163*** (0.0055) [−0.0342]	−0.0145 (0.0104) [−0.0303]
Married	−0.0072 (0.0062) [−0.0146]	−0.0089 (0.0077) [−0.0183]
Literacy	−0.0510*** (0.0076) [−0.1008]	−0.0065 (0.0102) [−0.0093]
Household size	0.0030*** (0.0006) [0.0722]	−0.0021 (0.0035) [−0.0320]
Household size squared	−0.0000*** (0.0000) [−0.0345]	0.0001 (0.0002) [0.0285]
Area of residence (urban)	−0.2523*** (0.0111) [−0.4325]	−0.1588*** (0.0161) [−0.3284]
Social capital	0.0117* (0.0062) [0.0191]	−0.0158 (0.0098) [−0.0332]
Self-employed	0.0296*** (0.0058) [0.0621]	−0.0031 (0.0103) [−0.0044]
Employed	−0.1379*** (0.0251) [−0.0748]	−0.0084 (0.0244) [−0.0076]
Constant	0.9106*** (0.0160)	0.8276*** (0.0225)
Age		
<i>First-Stage</i>		
Instrument (Time to reach the nearest mobile money agent)	−0.0037*** (0.0001)	−0.0021*** (0.0002)
F-statistic of first regression	612.356	108.104
Observations	5013	5045
R-squared	0.4860	0.1000
<i>Endogeneity test</i>		
Durbin (score) chi2 (1)	73.2022	11.187
Prob	0.0000	0.0008
Wu-Hausman F (1, 4999) / F(1, 5031)	76.5231	11.366
Prob	0.0000	0.0008
<i>Test of weakness of instruments</i>		
R-sq	0.3422	0.1159
Adjusted R-sq.	0.3406	0.1138
Partial R-sq	0.1504	0.0092
F (1, 5000) / F (1,5032)	612.356	108.104
Prob > F	0.0000	0.0000
<i>Weak-instrument-robust inference</i>		
Anderson-Rubin Wald test		
F (1,5000) / F (1,5032)	189.33	17.81
P-val	0.000	0.000
Anderson-Rubin Wald test		
Chi-sq (1) / Chi-sq (1)	189.83	17.85
P-val	0.000	0.000
Stock-Wright LM S statistic		
Chi-sq (1)	180.20	17.38
p-val	0.000	0.000

Robust standard errors in parentheses \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . Standardised coefficients are in square brackets.

Source: Authors' computation.

and more secure, mobile money can stimulate small-scale trade (Jack & Suri, 2014), which can contribute to improving household income.

As a secure means of storing value, mobile money promotes household savings, enabling households to smooth their consumption of modern and cleaner cooking fuels. In addition, mobile money can help to increase household electrification rates through simpler and faster payment of electricity bills (Coulibaly, 2023). Our results are consistent with those of previous studies that have highlighted poverty reduction through the adoption of mobile money (Djahini-Afawoubo et al., 2023; Lee et al., 2021; Suri & Jack, 2016; Yao et al., 2023). Furthermore, access to basic financial services (mobile money) remains an opportunity to improve household well-being and to reduce poverty (Apeti, 2022). In developing countries, where a large proportion of the population is excluded from formal financial services, the development of mobile telephones offers an alternative, and an opportunity, for poor households to access basic financial services via mobile money (Apeti, 2022; Coulibaly, 2023). This enables them to increase their savings rate, and consequently the opportunities for financial autonomy (Duflo, 2020), in order to cope with unforeseen short-term shocks (Demirgüç-Kunt et al., 2018) that may concern the purchase of electricity or gas for cooking.

Urban residence had a statistically significant effect on multidimensional energy poverty. There is a decrease in multidimensional energy poverty of  $-0.433$  standard deviations for urban residents compared to rural residents in Burkina Faso, and a decrease of  $-0.328$  standard deviations for Togo. This result is consistent with those reported in the literature (Djahini-Afawoubo et al., 2023; Oum, 2019).

Age has a positive effect on reducing energy poverty, while age squared has a negative effect on it. An increase in age per standard deviation is associated with a decrease in energy poverty of  $-0.182$  standard deviations, whereas an increase in age squared per standard deviation is associated with an increase in energy poverty of  $0.181$  standard deviations, resulting in a U-shaped relationship between age and multidimensional energy poverty. Thus, there is a given age at which the relationship between multidimensional energy poverty and age becomes positive.

Literacy has a positive effect on energy poverty reduction. The results indicate a reduction in energy poverty of around  $-0.101$  standard deviations for literate individuals compared to non-literate individuals. Literacy enables individuals to understand the importance and adoption of energy-efficient practices better. Indeed, literate people can read and assimilate information on how to reduce their energy consumption and adopt more efficient technologies. This can help to reduce energy poverty. Djahini-Afawoubo et al. (2023), Mdululi and Dunga (2021), and Oum (2019) also find that education positively affects poverty reduction.

The results also indicate a U-shaped relationship between household size and multidimensional energy poverty. In other words, for a small household, multidimensional energy poverty increases, whereas for large households, multidimensional energy poverty decreases as household size increases. This result corroborates with the findings of Koomson and Danquah (2021). Multidimensional poverty increases for small households owing to factors such as fixed costs remaining constant and higher proportional expenditure.

Social capital has a positive effect on multidimensional energy poverty. Our results indicate an increase in multidimensional energy poverty of  $0.019$  standard deviations for individuals with social capital compared with those without social capital. This result, which seems paradoxical, can be explained by the level of the quality of social capital. Communities with high levels of social capital are able to work better together to implement sustainable energy solutions. This reduced their vulnerability to energy poverty. Djahini-Afawoubo et al. (2023) found a non-significant negative effect of social capital on multidimensional poverty.

Multidimensional energy poverty decreases by  $-0.075$  standard deviations when the individual is an employee, and increases by  $0.062$  standard deviations for self-employed individuals. Similar results have been reported by Churchill et al. (2020). Employment allows individuals to have a stable income to cover their basic energy needs, such as electricity and transport. Access to employment can also facilitate investments in energy-efficient systems. This contributes to the efficient use of resources; however, self-employed workers tend to have irregular incomes because of the nature of their work, which can make it difficult to cover energy costs that are usually constant.

**Table 8.** Parameters estimates of the mobile money and multidimensional energy poverty equations.

Variables	(1)	(2)	(3)	(1)	(2)	(3)
	Burkina Faso			Togo		
	Multidimensional energy poverty			Multidimensional energy poverty		
	Selection equation Mobile money 1/0	Mobile money not adopted	Mobile money adopted	Selection equation Mobile money 1/0	Mobile money not adopted	Mobile money adopted
Age	0.0410*** (0.0072)	−0.0015** (0.0007)	−0.0029 (0.0022)	0.0515*** (0.0073)	−0.0005 (0.0011)	−0.0041 (0.0028)
Age squared	−0.0004*** (0.0001)	0.0000*** (0.0000)	0.0000 (0.0000)	−0.0006*** (0.0001)	0.0000 (0.0000)	0.0000 (0.0000)
Female	−0.2097*** (0.0472)	0.0001 (0.0047)	−0.0510*** (0.0136)	−0.3210*** (0.0406)	−0.0028 (0.0076)	0.0076 (0.0154)
Married	0.0830 (0.0544)	−0.0178*** (0.0055)	0.0155 (0.0146)	−0.0171 (0.0468)	−0.0101 (0.0078)	−0.0030 (0.0134)
Literacy	0.5475*** (0.0543)	−0.0366*** (0.0062)	−0.0486*** (0.0177)	−0.0922 (0.0593)	−0.0157 (0.0099)	0.0480*** (0.0180)
Household size	0.0218*** (0.0063)	−0.0004 (0.0007)	0.0075*** (0.0018)	−0.0254 (0.0214)	−0.0071* (0.0036)	0.0155*** (0.0061)
Household size squared	−0.0002** (0.0001)	0.0000 (0.0000)	−0.0001*** (0.0000)	0.0014 (0.0015)	0.0004* (0.0003)	−0.0009** (0.0004)
Urban	0.6458*** (0.0607)	−0.1873*** (0.0077)	−0.2984*** (0.0178)	0.5819*** (0.0445)	−0.1858*** (0.0093)	−0.1795*** (0.0240)
Social capital	0.1365** (0.0585)	0.0003 (0.0056)	0.0188 (0.0159)	0.2878*** (0.0411)	−0.0316*** (0.0075)	−0.0194 (0.0152)
Self-employed	0.0241 (0.0514)	0.0136*** (0.0051)	0.0629*** (0.0138)	0.0283 (0.0575)	−0.0095 (0.0104)	0.0100 (0.0162)
Employed	0.7841*** (0.2220)	−0.1979*** (0.0531)	−0.0511* (0.0293)	0.5518*** (0.0861)	−0.0328 (0.0220)	−0.0478*** (0.0247)
Time to reach the nearest mobile money agent <sup>5</sup>	−0.0119*** (0.0006)			−0.0133*** (0.0018)		
Constant	−1.3367*** (0.1528)	0.8879*** (0.0140)	−0.0069*** (0.0020)	−1.7146*** (0.1502)	0.8421*** (0.0226)	0.6706*** (0.1028)
Ins0	−2.0277*** (0.0128)			−1.5748*** (0.0212)		
Ins1	−1.4537*** (0.0327)			−1.5545*** (0.0386)		
r0	0.2942*** (0.0531)			0.4044*** (0.1201)		
r1	0.6535*** (0.1167)			0.2357 (0.2089)		
sigma0	0.3164*** (0.0017)			0.2071*** (0.0044)		
sigma1	0.2337*** (0.0076)			0.2113*** (0.0081)		
rho0	0.2860*** (0.0488)			0.3837*** (0.1024)		
rho1	0.5740*** (0.0782)			0.2315 (0.1977)		
Observations	5,013	5,013	5,013	5,045	5,045	5,045
Log likelihood	373.21424			−1699.814		
Wald chi2 (11)	729.72			517.09		
Prob > chi2	0.0000			0.0000		
LR test of indep. eqns. :	chi2(2) = 9.83 Prob > chi2 = 0.0000			chi2(2) = 62.24 Prob > chi2 = 0.0074		

Robust standard errors in parentheses \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

Source: Authors' computation.

#### 4.8. Sensitivity/robustness checks

We conducted several sensitivity checks to assess the robustness of the estimates. Table 8 presents the results of the ESR model estimates. In each country, column (1) presents the estimates of the factors influencing mobile money adoption, while columns (2) and (3) present the effects of mobile money adoption on multidimensional energy deprivation scores. The test of independence between the three equations, i.e., the likelihood ratio test in each country, is rejected in favour of a joint dependence of the error terms of the model, indicating that the selection and outcome equations are correlated, and

**Table 9.** Average level of multidimensional energy poverty; effects of treatment.

Burkina Faso			Togo		
Decision stage			Decision stage		
To adopt	Not to adopt	Treatment effects	To adopt	Not to adopt	Treatment effects
0.5757 (0.2471)	0.7689 (0.1403)	ATT = -0.1932*** (0.1209)	0.5425 (0.0951)	0.7459 (0.1013)	ATT = -0.2034*** (0.0363)
0.5495 (0.1386)	0.8175 (0.0724)	ATU = -0.2680*** (0.0749)	0.5306 (0.1032)	0.6872 (0.1128)	ATU = -0.1566*** (0.0408)

Standard deviation in parentheses \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

Source: Authors' computation.

that it is appropriate to estimate these three equations jointly. Our instrumental variable is significantly and negatively correlated with mobile money adoption in both countries. Thus, as expected, an increase in distance to the nearest mobile money branch is associated with a decrease in mobile money adoption. An additional analysis of the correlation coefficients shows that  $\rho_0$  is significant in the estimates carried out in both countries, which indicates that the multidimensional energy deprivation scores of non-adopters of mobile money are significantly different from those of a random household in the sample. The positive value of  $\rho_0$  in fact means that the multidimensional energy deprivation scores of non-adopters of mobile money are lower than those of a random household in the sample. The  $\rho_1$  is positive in the estimates for both countries but only significant in the case of Burkina Faso. This indicates that the multidimensional energy deprivation scores of Burkinabe households adopting mobile money are significantly different from those of a random household in the sample. The positive value of  $\rho_1$  means that the multidimensional energy deprivation scores of households adopting mobile money are lower than those of a random household in the sample.

Table 9 presents the average treatment effect estimates (ATT), which represent the overall effects of mobile money adoption on multidimensional energy deprivation scores. The results indicate that mobile money adoption significantly reduces household multidimensional energy deprivation scores by 19.32 percentage points for Burkina Faso and 20.34 percentage points for Togo. Table 9 also presents estimates of the average treatment effect on untreated individuals (ATU). The findings indicate that mobile money adoption by non-adopters would significantly reduce their multidimensional energy deprivation scores by 26.80 percentage points for the case of Burkina Faso and 15.66 percentage points for the case of Togo. These results offer an important basis for concluding that mobile money is an important alternative for reducing multidimensional energy poverty in developing countries.

We also tested the robustness of the results by testing the sensitivity of the estimates using other thresholds and weightings for the MEPI. For the initial measure of energy poverty, we used the conventional 0.33 threshold. However, for the sensitivity analysis presented in Table 10 we used alternative thresholds of 0.2 and 0.5, which are consistent with the literature (Adusah-Poku & Takeuchi, 2019; Churchill & Smyth, 2020; Koomson & Danquah, 2021). The results of the alternative thresholds, presented in columns 1 and 2 for Burkina Faso and in columns 4 and 5 for Togo, are consistent with our findings. Indeed, the results indicate a positive effect of mobile money on reducing multidimensional energy poverty, which means that our results are robust to alternative thresholds in both countries. We also note that the estimates based on different thresholds (0.2, 0.33, and 0.5) yield identical results for both Burkina Faso and Togo. We also tested the sensitivity using alternative weights for energy poverty. Thus, we assign an equal weight of 0.25 to each dimension of the multidimensional energy poverty index. The results indicate a positive effect of mobile money on the reduction of multidimensional energy poverty in both countries. This indicates that the regression with the equal-weighting scheme is consistent with our main results and confirms their robustness to alternative weighting schemes.

## 5. Conclusion and economic policy implications

This study analyses the effects of mobile money on alleviating multidimensional energy poverty. Initially, the Alkire and Foster (2011) method was employed to construct a composite Multidimensional Energy Poverty Index (MEPI). Subsequently, a linear regression model utilising instrumental variable strategy was applied to analyse the effect of mobile money adoption on energy poverty reduction. Additionally, the

**Table 10.** Estimates for alternative thresholds and weights for the energy poverty index.

Variables	Dependent variable: multidimensional energy poverty					
	Burkina Faso			Togo		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cut-off (0.2)	Cut-off (0.5)	Using equal weights	Cut-off (0.2)	Cut-off (0.5)	Using equal weights
Mobile money adoption	−0.2138*** (0.0162) [−0.4015]	−0.2138*** (0.0162) [−0.4015]	−0.2122*** (0.0162) [−0.4067]	−0.3373*** (0.0816) [−0.6275]	−0.3373*** (0.0816) [−0.6275]	−0.3584*** (0.0834) [−0.6821]
Age	−0.0030*** (0.0008) [−0.1819]	−0.0030*** (0.0008) [−0.1819]	−0.0027*** (0.0008) [−0.1687]	0.0015 (0.0015) [0.0966]	0.0015 (0.0015) [0.0966]	0.0019 (0.0015) [0.1292]
Age squared	0.0000*** (0.0000) [0.1811]	0.0000*** (0.0000) [0.1811]	0.0000*** (0.0000) [0.1774]	−0.0000 (0.0000) [−0.0807]	−0.0000 (0.0000) [−0.0807]	−0.0000 (0.0000) [−0.1142]
Sex (female)	−0.0163*** (0.0055) [−0.0342]	−0.0163*** (0.0055) [−0.0342]	−0.0147*** (0.0056) [−0.0315]	−0.0145 (0.0104) [−0.0303]	−0.0145 (0.0104) [−0.0303]	−0.0137 (0.0107) [−0.0293]
Married	−0.0072 (0.0062) [−0.0146]	−0.0072 (0.0062) [−0.0146]	−0.0118* (0.0064) [−0.0243]	−0.0089 (0.0077) [−0.0183]	−0.0089 (0.0077) [−0.0183]	−0.0164** (0.0078) [−0.0347]
Literacy	−0.0510*** (0.0076) [−0.1008]	−0.0510*** (0.0076) [−0.1008]	−0.0496*** (0.0077) [−0.1001]	−0.0065 (0.0102) [−0.0093]	−0.0065 (0.0102) [−0.0093]	−0.0098 (0.0104) [−0.0143]
Household size	0.0030*** (0.0006) [0.0722]	0.0030*** (0.0006) [0.0722]	0.0021*** (0.0007) [0.0507]	−0.0021 (0.0035) [−0.0320]	−0.0021 (0.0035) [−0.0320]	−0.0022 (0.0036) [−0.0342]
Household size squared	−0.0000*** (0.0000) [−0.0345]	−0.0000*** (0.0000) [−0.0345]	−0.0000 (0.0000) [−0.0196]	0.0001 (0.0002) [0.0285]	0.0001 (0.0002) [0.0285]	0.0001 (0.0002) [0.0274]
Area of residence (urban)	−0.2523*** (0.0111) [−0.4325]	−0.2523*** (0.0111) [−0.4325]	−0.2310*** (0.0108) [−0.4040]	−0.1588*** (0.0161) [−0.3284]	−0.1588*** (0.0161) [−0.3284]	−0.1382*** (0.0165) [−0.2924]
Social capital	0.0117* (0.0062) [0.0191]	0.0117* (0.0062) [0.0191]	0.0124** (0.0063) [0.0206]	−0.0158 (0.0098) [−0.0332]	−0.0158 (0.0098) [−0.0332]	−0.0110 (0.0100) [−0.0236]
Self-employed	0.0296*** (0.0058) [0.0621]	0.0296*** (0.0058) [0.0621]	0.0285*** (0.0059) [0.0611]	−0.0031 (0.0103) [−0.0044]	−0.0031 (0.0103) [−0.0044]	−0.0006 (0.0104) [−0.0009]
Employed	−0.1379*** (0.0251) [−0.0748]	−0.1379*** (0.0251) [−0.0748]	−0.1268*** (0.0247) [−0.0702]	−0.0084 (0.0244) [−0.0076]	−0.0084 (0.0244) [−0.0076]	−0.0003 (0.0248) [−0.0003]
Constant	0.9106*** (0.0160)	0.9106*** (0.0160)	0.8749*** (0.0163)	0.8276*** (0.0225)	0.8276*** (0.0225)	0.8084*** (0.0230)
<i>First-Stage</i>						
Instrument (Time to reach the nearest mobile money agent)	−0.0037*** (0.0002)	−0.0037*** (0.0002)	−0.0037*** (0.0002)	−0.0021*** (0.0002)	−0.0021*** (0.0002)	−0.0021*** (0.0002)
F-statistic of first regression	612.356	612.36	612.36	108.10	108.10	108.10
Observations	5,013	5,013	5,013	5,045	5,045	5,045
R-squared	0.4857	0.4857	0.4441	0.0528	0.0528	−0.0291
<i>Endogeneity test</i>						
Durbin (score) chi2 (1)	73.2022	73.2022	70.0831	11.187	11.187	12.8642
Prob	0.0000	0.0000	0.0000	0.0008	0.0008	0.0003
Wu-Hausman F(1, 4999) / F(1,5031)	76.5231	76.5231	73.1785	11.366	11.366	13.1655
Prob	0.0000	0.0000	0.0000	0.0008	0.0008	0.0003
<i>Test of weakness of instruments</i>						
R-sq	0.3422	0.3422	0.3422	0.1159	0.1159	0.1159
Adjusted R-sq.	0.3406	0.3406	0.3406	0.1138	0.1138	0.1138
Partial R-sq	0.1504	0.1504	0.1504	0.0092	0.0092	0.0092
F(1, 5000) / F(1,5032)	612.356	612.356	612.356	108.104	108.104	108.104
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
<i>Weak-instrument-robust inference</i>						
Anderson-Rubin Wald test						
F (1,5000) / F (1,5032)	189.33	189.33	184.56	17.81	17.81	19.47
p-val	0.000	0.000	0.000	0.000	0.000	0.000

(continued)



Table 10. Continued.

Variables	Dependent variable: multidimensional energy poverty					
	Burkina Faso			Togo		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cut-off (0.2)	Cut-off (0.5)	Using equal weights	Cut-off (0.2)	Cut-off (0.5)	Using equal weights
Anderson-Rubin Wald test						
Chi-sq (1) / Chi-sq (1)	189.83	189.83	185.04	17.85	17.85	19.52
P-val	0.000	0.000	0.000	0.000	0.000	0.000
Stock-Wright LM S statistic						
Chi-sq (1)	180.20	180.20	0.000	17.38	17.38	18.89
p-val	0.000	0.000	174.05	0.000	0.000	0.000

Robust standard errors in parentheses \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . Standardised coefficients are in square brackets.

Source: Authors' computation.

endogenous switching regression (ESR) model was used to check the robustness of the results. The results indicate a significantly higher incidence of multidimensional energy poverty in Togo than in Burkina Faso, and a higher intensity of multidimensional energy poverty in Burkina Faso than in Togo. Moreover, the results show a positive effect of mobile money adoption on the reduction of multidimensional energy poverty. This result is robust compared to quasi-experimental methods and other sensitivity checks, such as alternative thresholds for multidimensional energy poverty. Overall, the findings indicate that mobile money contributes to the reduction in multidimensional energy poverty in Burkina Faso and Togo; however, access to formal financial services remains a challenge in developing countries. In these countries, where a large proportion of the population is excluded from using formal financial services, our results support the view that mobile money is an effective policy alternative for reducing energy poverty, thus contributing to the attainment of Sustainable Development Goal 7, which aims to ensure household access to modern energy services.

Therefore, we advocate for the promotion of mobile money usage in developing countries to achieve reductions in energy poverty. Policies aimed at reducing or even exempting mobile money transactions from taxation could be an effective way of encouraging the use of mobile money in developing countries. Governments are encouraged to put in place the necessary structures to improve the coverage and quality of mobile phone networks on the one hand, and to decrease the average distance to travel to a mobile money branch on the other, especially in rural areas. Such efforts can incentivise the adoption of mobile money and mitigate the risk of energy poverty both presently and in the future. In line with Seng (2021), we will suggest that our policy-makers consider integrating financial education into the formal and non-formal education system with a particular focus on personal finance issues, such as budgeting, money management and financial planning in the context of mobile money. It is very important that policy-makers support the creation of dynamic mobile agency services that integrate the world's poor into financial markets and enable them to use and manage their own money (Donovan, 2012).

One of the limitations of this study is that our data do not allow for dynamic analysis as we are using cross-sectional data. Panel data are not available. In addition, although we assume that an increase in household income is the main channel for the impact of mobile money on reducing multidimensional energy poverty, our data do not allow us to test this hypothesis. Addressing this limitation and utilising more appropriate data, such as panel data, will serve as the basis for future research.

### Authors' contributions

All the authors contributed to the design and development of the study. The methodological part and analysis of the results were written by COMPAORE Dimaviya Eugène and Maiga Boukaré. The introduction and literature review were written by Asmo Guira. All authors have read and approved the final manuscript. All authors accept responsibility for all aspects of their work.

### Disclosure statement

No potential conflict of interest was reported by the author(s).

## Notes

1. International Energy Agency.
2. National Institute of Statistics and Demography (INSD)/Burkina Faso.
3. National Institute of Statistics and Economic and Demographic Studies (INSEED)/Togo.
4. Central Bank of West African States (BCEAO).
5. Instrumental variable (IV).

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## Data availability

The data that support the findings of this study are available from the corresponding author, [COMPAORE Dimaviya Eugène], upon reasonable request.

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## Appendix

**Table A.** Robustness results of MEPI measures.

k (cut-off)	Burkina Faso		Togo	
	H	MEPI	H	MEPI
0.2	0.954***	0.752***	0.982***	0.646***
0.33	0.907***	0.740***	0.911***	0.628***
0.4	0.907***	0.740***	0.911***	0.628***

Note. 0.33 is the baseline cut-off used in the main results. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table B.** Robustness results of MEPI measures by area of residence.

k (cut-off)	Burkina Faso				Togo			
	Rural H	Urban H	Rural MEPI	Urban MEPI	Rural H	Urban H	Rural MEPI	Urban MEPI
0.2	0.999***	0.784***	0.833***	0.447***	0.996***	0.971***	0.783***	0.550***
0.33	0.995***	0.578***	0.832***	0.395***	0.983***	0.860***	0.780***	0.522***
0.4	0.995***	0.578***	0.832***	0.395***	0.983***	0.860***	0.780***	0.522***

Note. 0.33 is the baseline cut-off used in the main results. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table C.** MEPI measures based on rank sum weighted method.

	Energy Poverty (Baseline)		Energy Poverty (Rank Sum Weighted)-1		Energy Poverty (Rank Sum Weighted)-2	
	H	MEPI	H	MEPI	H	MEPI
Burkina Faso	0.907***	0.740***	0.932***	0.830***	0.932***	0.815***
Togo	0.911***	0.628***	0.944***	0.704***	0.944***	0.613***

Note. Energy Poverty (Rank Sum Weighted)-1 is based on the cooking, lighting and other measures, ordering of dimensions, and Energy Poverty (Rank Sum Weighted)-2 is based on lighting, cooking and other measures. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .

**Table D.** MEPI measures based on rank sum weighted method by area of residence.

	Energy poverty (baseline)		Energy poverty (rank sum weighted)-1		Energy poverty (rank sum weighted)-2	
	H	MEPI	H	MEPI	H	MEPI
<i>Burkina Faso</i>						
Urban	0.578***	0.395***	0.685***	0.494***	0.685***	0.435***
Rural	0.995***	0.832***	0.999***	0.920***	0.999***	0.916***
<i>Togo</i>						
Urban	0.860***	0.522***	0.910***	0.604***	0.910***	0.482***
Rural	0.983***	0.780***	0.991***	0.847***	0.991***	0.800***

Note. Energy Poverty (Rank Sum Weighted)-1 is based on the cooking, lighting and other measures ordering of dimensions and Energy Poverty (Rank Sum Weighted)-2 is based on lighting, cooking and other measures. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ .