Left in the Dark:

Analysis of Household Energy Poverty on Human Development Outcomes in South Africa, Using the National Income Dynamics Survey (NIDS)

Masters Dissertation

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Abstract

Despite progress in post-Apartheid South Africa's electrification rates, especially in the country's rural areas, widespread energy poverty persists at the household level. To understand the dynamics of energy poverty at the micro-level, this dissertation examines how two different measures of energy poverty – namely, the Multidimensional Energy Poverty Index (MEPI) and the Ten-Percent Threshold measure (TPT) – affect human development outcomes in the domains of health, labour market outcomes and education-related outcomes. The MEPI is constructed using a range of dimensions relating to access to modern energy services captured in a nationally representative panel dataset, the National Income Dynamics Survey (NIDS). I also construct the TPT using variables pertaining to household energy expenditure and income. Although there were improvements from 2008 to 2017, it was found that multi-dimensional energy poverty is still prevalent in South African households, especially in rural and low-income households. The dissertation then turns to regression methods to establish whether there is an effect between energy poverty and human outcome indicators. I run both OLS and FE estimation strategies. However, empirical tests and prior literature points to the issue of potential endogeneity within the energy poverty variable. I utilize district-level electricity price and the percentage of households in the district using biomass as a fuel source as instrumental variables to correct for the endogeneity issue. Using a 2SLS regression model, the findings reflect that multidimensional energy poverty does indeed have adverse consequences for an adult individual's health outcomes – both for subjective and objective measures. The results also point to the negative effect of household energy poverty on an individual's likelihood to participate in the labour force and be in employment. These results are all highly significant. Lastly, I establish that multidimensional energy poverty is associated with lower number of school years and higher likelihoods of missing a school day. I also show that energy poverty has a gendered effect, with women in the household often experiencing worse outcomes. The TPT is used in a sensitivity analysis. Overall, the results from the investigation can assist in advising policymakers on how access to modern, clean energy sources can help individuals' development outcomes in South Africa.

Keywords: energy poverty, development outcomes, instrumental variable, national income dynamics survey

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List of Abbreviations

Body Mass Index	BMI
Continuing Sample Members	CSM
Department of Energy	DoE
Department of Minerals and Energy	DME
Energy Sector Management Assistance Programme	ESMAP
Energy Development Index	EDI
Energy Poverty	EP
Energising Development	EnDev
Fixed Effects	FE
Free Basic Electricity	FBE
General Household Survey	GHS
Gross Domestic Product	GDP
Human Development Index	HDI
Inclining Block Tariff	IBT
Integrated National Electrification Programme	INEP
Integrated Resource Plan	IRP
Instrumental Variable	IV
International Energy Agency	IEA
Liquified Petroleum Gas	LPG
Low-Income High Costs	LIHC
Multidimensional Energy Poverty Index	MEPI
Multidimensional Energy Poverty	MEP
Multi-tier energy access Tracking Framework	MTF
National Electrification Programme	NEP
National Income Dynamics Survey	NIDS
National Regulator South Africa	NERSA
Ordinary Least Squares	OLS
Oxford Poverty and Human Development Initiative	OPHI
Photovoltaic	PV
Pooled Ordinary Least Squares	POLS
Solar Home System	SHS
Sub-Saharan Africa	SSA
Sustainable Development Goal	SDG
Random Effects	RE
Temporary Sample Members	TSM
Ten-Percent Threshold	TPT
Two-Stage Least Squares	2SLS
World Health Organisation	WHO
United Nations	UN

Quotations

Sen (2014):

"Making it easier to produce energy with better environmental correlates (and greater efficiency of energy use) may be a contribution not just to environmental planning, but also to making it possible for a great many deprived people to lead a fuller and freer life."

UN Secretary General Ban Ki-Moon (UN, 2012):

"[energy is] … the golden thread that connects economic growth, social equity, and environmental sustainability".

"We need to tackle energy poverty."

Chapter 1. Introduction

1.1. Energy Poverty in South Africa

1.1.1. Introduction and Purpose of Study

Energy poverty has become a pressing challenge in the development arena. Roughly 1.06 million people internationally lack access to electricity. This circumstance mostly describes people living in rural areas in African countries, where 588 million individuals do not have electricity (International Energy Agency [IEA], 2017). Due to the unavailability and inaccessibility of modern, clean energy sources faced by developed and developing nations alike, academic literature and reputable international organisations (IEA,2012) developed the concept of energy poverty. Against this backdrop, the United Nation's (UN) Sustainable Development Goal (SDG) 7 was formulated as a focal point for nations to "ensure universal access to affordable, reliable and modern energy for all by 2030" (UN, 2018). Clean and modern energy access is the cornerstone of sustainable development and can assist with the achievement of the other 16 SDGs (Sambodo & Novandra, 2019). Despite the attention that energy poverty receives in the current literature, there still remains a gap in the understanding of what energy poverty is and what it means for policy-makers (Lin & Okyere, 2020). According to Phoumin and Kimura (2019), the lack of consensus regarding the definition of energy poverty presents itself as an obstacle to SDG 7's progress.

One might wonder why choose to focus on energy poverty as opposed to income poverty. Access to modern energy pervades all aspects of poverty and is a phenomenon that may be both a consequence and cause of income poverty. Moreover, Grossman & Trubina (2021) argue that the concept of energy poverty is inextricably linked to individual dignity. Secondly, income poverty and energy poverty do not necessarily overlap – especially in countries where cultural, geographical and climatic conditions vary (Kandkher et al., 2012; Wang et al., 2015). For instance, Kandkher et al. (2012) looking at rural India, found that 57% of households were energy poor, whilst 22% of households were income poor.

Lastly, due to the complexity in program design and initiatives involved in tackling energy poverty – which requires large capital outlay and infrastructure investments, especially on the side of the state, energy poverty is worthy of separate attention. In this regard, policy measures differ to standard and mainstreamed practices of alleviating income poverty by fiscal means

(for example, taxation and social security schemes). Furthermore, energy-related issues are inextricably linked with pressing environmental concerns (Vermaak et al., 2009). The focus on energy poverty as an attempt to address energy impoverished households, through enhanced energy production capacity would cause an increase in carbon emission, thus contributing to the pressing problem of climate change (Kaygusuz, 2011; Urge-Vorsatz & Herrero, 2012). In sum, there exists an implicit trade-off between energy poverty alleviation and reduced fossil fuel emissions (Urge-Vorsatz & Herrero, 2012).

South Africa has not yet transitioned into a nation with "universal modern energy access for all", despite its looming goal to achieve this status by 2030 (Department of Energy (DoE), 2009). As of 2016, the residential sector accounts for 8% of South Africa's energy demand (DoE, 2019). Despite its large electrification rates and energy interventions, approximately 15% of households are not connected to the national electricity grid – let alone number of households who are predominately reliant on traditional and unclean energy resources Reportedly, 7.7% of households use firewood for cooking purposes. This circumstance is particularly prevalent in the Limpopo province (31.6%) and Mpumalanga (16.2%) (StasSA, 2019). South Africa is an interesting case to consider due to its high levels of grid coverage, high poverty rates (a poverty head count of approximately 55%) and the large percentage rural households relying on traditional fuels. In sum, in South Africa, energy poverty is an obstacle despite its higher electricity rates relative to the rest of SSA (Israel-Akinbo et al., 2018).

This study's purpose is two-fold: first, an understanding of energy poverty dynamics in South Africa is developed. South Africa offers an interesting case for filling this gap because, despite a documented electrification rate of 86% in 2018 (Israel-Akinbo, 2018), the rates of traditional fuel usage in rural areas are overwhelming. Approximately one third of South Africans households cook mostly with traditional fuel sources (Vegter, 2016). This allows for a nuanced discussion regarding the type of energy poverty indicator, looking at both unidimensional and multidimensional indicators, that ought to be utilised in South Africa. Secondly, the dissertation will contribute to an enhanced understanding of the potential synergies and/or trade-offs between access to clean, modern energy and sustainable development. Previous studies have provided evidence that household energy poverty can result in the increased likelihood of individual depression (Lin & Okyere, 2020), ill-health (Zang et al., 2019), a child missing school (Karim et al., 2018) and labour force participation amongst females (Dinkelman, 2011). Although prior literature has divulged the topic of energy poverty, with particular emphasis on

household electricity connection, little is known about its associations between welfare outcomes at the individual level in South Africa.

1.1.2. History of South Africa's Energy Sector and Key Regulation

The South African government has acknowledged the importance of access to energy in tackling wide-spread poverty (DoE, 2009). These sentiments were first expressed in the South African Energy White Paper (South Africa, 1998), which articulated that "*energy security for low-income households can help reduce poverty, increase livelihoods and improve living standards"* (1998: ix). South Africa's commitment to improving energy welfare is made evident by the fact that, in contrast to the rest of Sub-Saharan Africa (SSA), South Africa has one of the highest electrification rates relative to its African counterparts. Access to electricity, for instance, has increased from 76,7% in 2000 to 84,7% in 2018 (StatsSA, 2019), whereas this percentage drops to 46.7% when looking at SSA as a whole (World Bank, 2020).

Upon the end of the apartheid regime, the newly elected democratic government faced the challenge of addressing 60% of the population being without access to electricity, with access rates in rural areas being substantially less. During apartheid, public service delivery - such as piped water, sanitation and electricity – was skewed towards the white minority and was denied to the majority of African households, especially those residing in the former homelands (Bhorat & van der Westhuizen, 2013; Gaunt, 2003). This sparked the establishment of the National Electrification Programme (NEP) by Eskom, South Africa's national electricity utility, which aimed to provide electricity access to households that had not had access during Apartheid.

The NEP was successful in meeting its targets (DoE, 2009): 2 million households, representing approximately one quarter of the country's households, were grid-connected by 2001. Eskom's achievement in reaching its electrification targets can be viewed as strategic: as the nation's main electricity provider, it aimed to reduce competition in the market for electricity generators and distributors and signal its capability to the newly formed government (Dinkelman, 2011).

The NEP was thereafter replaced by the Integrated National Electrification Programme (INEP) (2001 – 2010); the INEP focused on rural electrification, as urban electrification previously dominated the NEP's objectives, and it included annual targets of providing electricity to at least 300,000 households for five years. The overarching target was to reach universal energy access by 2012 (DoE, 2009). Throughout the duration of the program, energy interventions were put in place to reach households that were situated outside of Eskom's grid's range. This

included both providing solar home systems (SHS) to rural, indigent households as a part of the non-grid electrification programme and implementing the Free Basic Alternative Energy Subsidy of R40 per month[1]. The Free Basic Electricity (FBE)[2] subsidy, on the other hand, was introduced in 2003 and targets poor, grid-connected households and provides them with 50kWh of free electricity per month (DoE, 2009; Davis, Hughes & Louw, 2008). There has been much dispute as to the adequacy of such subsidies to meet basic needs and whether poor households actually possess the adequate infrastructure to utilize FBE (Ruiters, 2009; Ferriel, 2010).

The Integrated Resource Plan (IRP), published by the Department of Minerals and Energy (DME), was formulated in 2010 in terms of the National Energy Act, 2008 (Act No. 34 of 2008) (DoE, 2016). It was implemented to ensure a sustainable plan for South Africa's energy security in a way that a.) assists in alleviating poverty, and b.) contributes to the least impact on the environment (DoE, 2016). The plan places particular emphasis on the use of more renewable energy resources, especially in areas that are not grid-accessible.

However, despite South Africa's policy progress and evident commitment to household energy welfare, only 65.7% of households rated their quality of electrical supply services as 'good' in 2018 (StatsSA, 2019). This may be attributed to presence of 'load-shedding' schedules. 'Load-shedding' is used to describe Eskom's challenge in provisioning an adequate supply of electricity in South Africa due to Eskom's inability to meet electricity demand. This situation is mainly due to generation capacity and coal quality issues that was experienced country-wide in 2007/08 (Bohlman & Inglesi-Lotz, 2021). Furthermore, South African municipalities are the entities responsible for the provision of electricity, purchased from Eskom, to households (Eberhard, 2003); however, local municipalities are fraught with financial burdens and insufficient technical and regulatory capacity, resulting in inadequate electricity distribution (Tait, 2015).

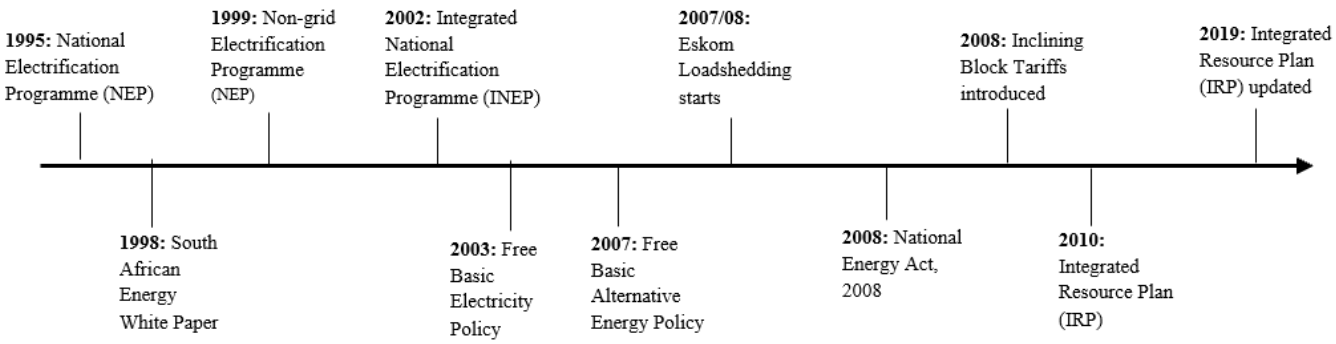
Furthermore, the country's electricity prices, although initially praised internationally for its low levels prior to 2008, have been increasing at a greater rate than inflation since 2012 (Dlamini, 2015). In 2008, with the objective of shielding low-income residential consumers from electricity price increases, NERSA approved the implementation of Inclining Block

[1] The adoption of the FBAE policy has been low – in 2014, only 10% of informal unelectrified households in South Africa has received the subsidy (StatsSA, 2014).
[2] Households registered as "indigent", along with other varying conditions, by the requisite local municipality are able to receive the 50kWh under the FBE. Municipalities have considered 150 kWh as the threshold when deeming a household 'indigent' or not (Ruiters, 2009).

Tariffs[3] (IBTs) by municipalities (Smart Energy International, 2012). In fact, recent evidence reports point to the imminent electricity tariff increase of 15% set for 2021 (Molefe, 2021). Load-shedding and increases in electricity prices undoubtedly impact lower-income households' abilities to use clean, modern energy resources.

Figure 1 below is a snapshot of the preceding discussion. It provides a timeline indicating the introduction of the regulations and policies presented in South Africa's post-Apartheid period. The reason that this time window is discussed is two-fold. Firstly, the residential energy policy interventions witnessed upon democratisation placed an emphasis on addressing the past injustices and servicing the population previously denied access (Winkler et al., 2008). This Secondly, this time window looks at the 10 years preceding the first wave and the subsequent waves of the National Income Dynamics Survey (NIDS), which is used in the study. This sub-section intended to provide historical insight to South Africa's current residential energy poverty situation.

Figure 1 Timeline depicting Key Energy Policies and Regulation in South Africa



Source: Gaunt, 2003; Monyei et al., 2018

1.1.3. The Structure of the Dissertation

This dissertation is made up of six chapters. In Chapter 2, I will extensively analyse existing literature on energy poverty indicators in an attempt to establish an appropriate measure applicable to South Africa's context. Measuring energy poverty is the first step to informing

[3] IBTs break down the price of electricity into several steps whereby the first step is set at the lowest price. As a consumer purchases more electricity, the consumer will move onto a higher step set at a greater price (DoE, 2013).

policy in alleviating energy poverty (Wang et al., 2015). Literature points to two types of energy poverty indicators – namely, the unidimensional approach and the multidimensional approach. Unidimensional indicators capture issues of accessibility or affordability by using a single metric. Multidimensional indicators take the stance that energy poverty is multidimensional in nature, thus considering the simultaneous issues of access to multiple energy types, affordability and efficiency. I provide a discussion of the various measures that fall under either category. This allows me to draw a conclusion as to which measure(s) are best suited for the purpose of the study. Chapter 2 further presents a discussion on the previous literature regarding factors driving energy poverty and its association with human welfare outcomes. Both a comprehensive indicator to recognize the energy poor and an understanding of how the provision of energy resources can influence an individual's welfare in South Africa are lacking at a policy level. In Chapter 3, I undertake a comprehensive assessment of South Africa's energy poverty scenario using household and individual panel data from all five waves, spanning from 2008 to 2017, of the National Income Dynamics Study (NIDS) dataset. Using both the Ten-Percent Threshold (TPT) indicator and Multi-dimensional Energy Poverty Index (MEPI), I analyse the dynamics across the ten-year period. The data description suggests that, employing both energy poverty measures, the proportion of the population in energy poverty has been steadily declining between 2008 and 2010. I further consider preliminary associations between these energy poverty indicators and human welfare outcomes. Chapter 4 provides an overview of the methodology. By employing a panel fixed effects model (FE), the panel nature of the dataset is exploited. This model controls for unobserved heterogeneity and omitted variable bias. However, previous authors caution against the issue of endogeneity present in the energy poverty variable when using these models. After reviewing, previous energy poverty models, I find that electricity price and the percentage of the population using biomass fuels are appropriate instrument variables (IV) for energy poverty. I therefore use a two-stage least squares model (2SLS). Chapter 5 presents and provides a discussion of the empirical results. The results are divided into three sections: adult health outcomes; adult labour market outcomes, and child health and education outcomes. The overall findings point to the adverse effect household energy poverty has on an individual's development outcome. When disaggregated by gender, I observe that energy poverty causes a greater likelihood of depression and adverse labour market outcomes in women, compared to their male counterparts. I also include various robustness checks and touch on the study's limitations. Lastly, Chapter 6 concludes with the study's limitations and policy implications from the findings.

Chapter 2. Literature Review

2.1. Energy Poverty Indicators

2.1.1. Definitions of Energy Poverty

The definitions of energy poverty have evolved over the last three decades. The concept of energy poverty was originally coined by Lewis (1982) in which he attempted to describe the effect that insufficient access to energy sources could have on people's welfare. Early energy poverty researchers, such as Lewis (1982) and Boardman (1991), mainly sought to describe the inability of households to maintain adequate indoor temperatures due to issues of affordability, household budget constraints and energy inefficiency. In a similar vein, Leach (1992) demonstrated that lower income households had a higher energy consumption to household income ratio relative to high income households.

Despite the contributions of numerous academics, the definition of energy poverty is not universally used and accepted. The overriding consensus points to inadequate levels of energy consumption that cannot support basic human needs (Gonzales-Eguino, 2015). Day et al. (2016: pg.) provides a definition of energy poverty as a:

"Situation of inability to realize the essential capabilities as a result of insufficient access to affordable, reliable and safe energy services[4], and taking into account the alternative means of realising these capabilities in a reasonable manner".

Unpacking this definition, we see that there are three components to the sufficient provision of modern energy services – namely, affordability, safety and reliability (Tait, 2017). For the purpose of this study, it is important to distinguish traditional sources of energy, mostly utilised by energy deprived households, from modern energy sources. 'Modern' fuels include electricity, liquefied petroleum gas (LPG), and biofuels. Based on the energy ladder hypothesis, charcoal and kerosene are classified as 'intermediate' fuels, whilst 'traditional' fuels encompass wood, agricultural waste and animal dung, and are considered less cleaner, less reliable and less efficient compared to intermediate and modern fuels (UNDP, 2005; World Bank, 2012). In poorer countries, the choice of the energy source tend to be limited (Gonzales-Eguino, 2015; Bailis, 2011). Low-income households in developing contexts proportionally

[4] Energy services refer to the "application of useful energy to tasks desired by the consumer", such as heating, cooking or lighting (Nussbaumer, 2012; pg. 3).

utilise traditional fuels and less electricity and LPG (Reddy, 2000). With regards to affordability, the 'energy ladder' hypothesis posits that households will transition to cleaner, more modern energy services as their incomes grow (Crentsil et al., 2020).

Studies have indicated that the low-quality energy services are not always the cheapest, and thus energy expenditures may still form a large proportion of low-income household's budget allocation, even if it is more readily available and of lower quality than alternative sources (Foster et al., 2000). Furthermore, what is considered as a 'just and sustainable' energy system is also controversial (Samarkoon, 2019). The institutional framing of traditional biofuels as negatively impacting both health and the environment may be overstated and not all 'modern' energy sources, such as LPG, are as clean as originally thought (Chatti et al., 2017).

Traditional literature on the matter has divided energy poverty into 'fuel poverty' and 'energy deprivation' in developed and developing countries respectively (Day et al., 2016). Li et al. (2014) argues against using these terms interchangeably: 'fuel poverty' should pertain to the affordability of adequate energy services to maintain a certain ambient temperature in colder climates, whilst 'energy poverty' describes the situation of households lacking means to maintain subsistent levels of energy consumption. It is important to make this distinction on the outset, as literature often conflates the two, although it is evident that they rely on starkly different contexts.

Before tackling the variety of available indicators, it is necessary to briefly highlight the features that are necessary for an energy-based poverty indicator (Vermaak et al., 2009). Looking to Kanjee and Dobie (2003: 31)'s features for a good indicator, we see that they consider: availability and reliability of the data; reason for why an indicator is required; the report's scope for which it will be used; and , the institutional level in which the indicator will be used. Atkinson et al. (2002) similarly asserts that a good indicator rests on six principles: clarity; robustness; policy responsiveness; comparability and consistency; timeliness and succinct information. In considering the appropriate indicator for the South African context, the above-discussed recommendations form good starting points.

2.1.2. Unidimensional Indicators

When regarding developing countries, indicators are constructed to capture the issue of modern energy sources' accessibility, which falls under supply-side approaches[5] (Pachauri & Spreng, 2011). Dependent on a household's energy needs and benefits derived from energy services, the International Energy Agency (IEA) (2009) describes the levels of access to energy services, namely (Ismail & Khembo, 2015):

1. Minimum levels of energy access to meet subsistence needs (such as heating, health, education, cooking and community services).
2. Energy access levels that will enable households to meet modern society needs and improve productivity levels (e.g., modern sources for domestic appliances, cooking and transportation).

Available datasets often include questions pertaining to questions of access to electricity, national grid connection and LPG, and whether households still rely on solid fuels to satisfy their basic energy needs. In this instance, there are numerous studies that look at the question of electricity access (Dinkelman, 2011; Matinga & Annegarn, 2013; Rathi & Vermaak, 2018) and studies have indicated that access-adjusted approaches are more robust and informative than the expenditure approach[6] (Kohler et al., 2009). However, access approaches can be ambiguous as there is no clarity as to whether it considers household fuel availability or the physical presence of energy carriers (Pachuari, 2011).

Authors on the subject of energy poverty in developed countries mainly centre their research on the energy affordability issue (Boardman, 1991; Liddell & Morris, 2010; Okushima, 2016). The TPT was originally proposed by Boardman (1991): if an individual's expenditure on energy resource amounts to more than 10% of their income, then that person is deemed energy poor. The energy poverty line is set to distinguish those in energy poverty and those not; it is set at an energy consumption level which enables a household to maintain a basic standard of living (Barnes et al., 2010; Ozughalu & Ogqumike, 2018). The expenditure-based approach is predicated on the fact that poorer households generally allocate a larger proportion of their

[5] Supply-side approaches pertain to "the physical availability of modern energy sources, physical energy requirements and reliability of energy supply" (Le Roux & Chourmet-Nkolo, 2021).
[6] The access-adjusted approach is derived by summing the quantity of energy used per household and adjusting for the various types of household energy sources. A weighting system reflects the relative energy efficiencies. The expenditure approach, on the other hand, refers to the proportion of household expenditure allocated to energy expenditures (Kohler et al., 2009).

expenditure to energy and food items. By virtue of this reasoning, if energy prices rise, many households would be forced into undue hardship (Barnes et al., 2011). This expenditure approach is endorsed by South Africa's Department of Energy (DoE) (2013), whereby a middle-income household, earning approximately R10,000, is deemed energy poor if its energy expenditure amounts to R1,000 – R1,500 (in (Ismail & Khembo, 2015).

However, academics suggest that the 10%-15% threshold indicator is not scientifically informed; perhaps because it is based on the context of the United Kingdom, and therefore it cannot be used generally across countries (Healy & Clinich, 2004). Furthermore, since data mainly asks questions regarding electricity and LPG expenses, the indicator often overlooks the cost associated with ensuring adequate energy infrastructure (Atsalis et al., 2016: pg. 3). Academics have called for a movement away from the 10% threshold as it is both sensitive to energy price fluctuations and other technical considerations, such as the inaccuracy of income reporting encountered in many countries (Hill, 2011). The British government has since endorsed the Low-Income High Costs (LIHC) indicator – which combines both a threshold regarding income and energy costs, identified using the median modelled bill, to assess both the extent and depth of fuel poverty (Department of Energy & Climate, 2016). To utilize the LIHC indicator, data is needed on both energy prices and the energy requirements of a household.

The TPT may not be applicable to the context of developing countries for two reasons. Firstly, individuals residing in low-income countries have less disposable income, and thus a higher proportion of income is de facto allocated towards basic necessities. Secondly, more people are likely to live in rural areas where they rely more on solid biomass for fuel, which is costless (Zang et al., 2019). Kohler et al. (2009) illustrate the above point with the following example: if two households, A and B, both spent more than 10% of their income on energy expenditure, they are equally classified as 'energy poor'. However, what the expenditure approach fails to consider is that household A's energy expenditure constitutes candles and paraffin, whilst household B uses electricity. Electricity is a more efficient and cleaner energy resource than candles and paraffine, and thus it is illogical to classify both households as equally energy deprived. Likewise, a study on the relationship between energy poverty and household income in Bangladesh suggests that there may be other factors besides income poverty that contributes to energy poverty (Barnes et al., 2011).

Demand-side indicators[7] are also available and set thresholds for energy-consumption levels. For instance, according to IEA (2012), the regional average electricity consumption can be used as a standard for basic electricity needs. In 2017, the IEA (2017) set the minimum consumption threshold at 250 kWh/ annum and 500 kWh/ annum for rural and urban households respectively. Barnes et al. (2011) adopts a similar approach by defining the energy poverty line as the minimum threshold at which energy consumption rises with increases in income. These two examples are responsive to the changes in income levels and the dynamic nature in which the economy operates.

However, the limitation of the demand-side indicator exists in its practicality and cost-effectiveness as it is expensive and time-consuming to collect and monitor data (Tait, 2017). Furthermore, Battacharyya (2012) notes that setting the threshold at the regional average may promote wasteful, unsustainable consumption in some instances, and inadequate levels in other cases. Either way, what is considered to be the minimum quantity of energy to meet essential human needs is often inherently subjective and hinges on a contextual analysis (Battacharyya, 2012; Tait, 2017; Pachuari, 2011).

2.1.3. Multidimensional Indicators

In contrast to perceiving energy poverty as a binary indicator or money metric, as indicated by the preceding discussion, one can regard energy poverty as a multidimensional concept that has bearing on numerous aspects of life. Amartya Sen's (1999) capability approach underpins the idea that energy poverty has an essential multidimensional role in promoting overall welfare in society and thus should be viewed in a comprehensive manner. The definition of energy poverty provided in sub-section 1.1. highlights the absence of choice that comes with being energy poor. These sentiments fall in line with those of Sen (1999) in that individuals are excluded from options that would enable them to choose, and thereby the freedom to choose, a dignified life (Gonzales-Eugino, 2015). An individual is deprived of a particular capability when she/he is denied this freedom to choose.

The capabilities approach has been considered when drafting multi-dimensional conceptions of energy poverty. Previous authors (Kandkher et al., 2012; Wang et al., 2015; Sadath & Acharya, 2017) have justified the view of energy poverty in this regard and, in line with Sen's

[7] Demand-side indicators "involves collection of data from electricity users through household energy surveys and the use of sensor-based instrumentation" (ESMAP, 2015; pg. 80).

sentiments, that income parameters are not the only means to measure a nation's development. An individual's ability to translate income into wellbeing is dependent on certain factors, such as their energy poverty status. Energy poverty is a direct afront to Sen's *economic facilities*[8], and thus to the advancement of an individual's general capability (Day et al., 2016). As discussed in sub-section 4 below, contaminated kitchen stoves can lead to indoor air pollution, a cause of respiratory diseases, denying individuals the freedom to a healthy life (Sadath & Acharya, 2017; IEA, 2017). Therefore, energy poverty describes a household's deprivations in energy-related dimensions, which can influence an individual's functionings (such as health) and the capability to function.

Nussbaumer (2003) similarly contends that sustainable economic development needs to look beyond measures of wealth and rather look to the broader means that ensure an individual's 'flourishing' (Day et al., 2016). Her infamous multi-dimensional energy poverty index (MEPI) is premised on the capabilities approach and is adapted from the Oxford Poverty and Human Development Initiative (OPHI)'s multi-dimensional poverty index[9] (Alkire & Foster, 2011; Nussbaumer et al., 2012). The MEPI is built on various binary household indicators – such as having access to the following: modern cooking fuel, electricity, refrigerator, TV/ radio and a phone. Each household indicator is then weighted according to its relative importance in addressing basic needs and, upon summation of the indicators, a score is derived. If the score is less than 0.3, the household is considered energy poor (Nussbaumer et al., 2012). The MEPI approach is regarded by various authors as the suitable metric to capture energy poverty (Crenstil et al., 2019; Israel- Akinbo et al., 2018; Sadath & Acharya, 2017).

Recently, the World Bank (2020), through the Energy Sector Management Assistance Program (ESMAP), devised the multi-tier energy access Tracking Framework (MTF). The MTF is devised to regard various aspects (such as reliability, convenience, safety, adequacy *et cetera*) of energy applications required in a household. The MTF considers energy access for the following three components: electricity; cooking solutions; and space-heating solutions. According to each component, 'access', with reference to energy supply characteristics that influence a household's experience, ranges from no access (Tier 0) to full access (Tier 5), which accounts for whether the energy source is affordable and/or reliable (ESMAP, 2015). However,

[8] One of the five instrumental freedoms proposed by Sen (1999, pg. 10)
[9] The OPHI's multidimensional poverty index regards poverty as a state of multiple deprivations (Alkire & Foster, 2011).

the MTF prescribes the need for household data that comprehensively deals with energy access-related variables, which is unlikely to be readily available.

The IEA formulated the energy development index (EDI) to capture the regional implementation of modern energy sources. The EDI follows a similar form to the human development index (HDI). The HDI is constructed out of four indicators – namely, per-capita commercial energy consumption; per-capita residential electricity consumption; the share of modern fuels in total residential sector energy use and the share of population with access to electricity (IEA 2010). However, this index neglects to consider energy contexts at household level, and thus is not suited for measuring energy poverty (Khatib, 2011).

Some studies construct measures to reflect both accessibility and accessibility issues (Zang et al., 2019; Sadath & Acharya, 2017). Zang et al. (2019) equally weights a dummy variable reflecting the usage of solid fuel and an energy-expenditure threshold to reflect a multidimensional measure of energy poverty. The authors note (Zang et al., 2019: pg. 75) that equal weighting of dimensions may be easily generalized and allows for straightforward interpretations.

2.1.4. Practical Limitations

A study done by Bensch (2013) highlights how various energy poverty metrics can produce vastly different results regarding the identification of the energy poor and data requirements. The author makes use of five energy poverty metrices – namely, the *minimum energy consumption threshold approach*; the MEPI; the *income-invariant energy demand*; the *Correlation Sensitive Energy Poverty Index* (CSEPI) and the *Total Energy Access* (TEA) – across a sample of countries across SSA. Findings pointed to the consistent estimates of the MEPI, TEA and *Minimum Energy Consumption Threshold* indices.

The dominant trend in energy literature is the conception of energy poverty from the supply-side. Although the above-mentioned indicators that deal with the penetration rates of modern energy resources offer the benefits of comparability and simplicity in interpretation, they are often limited with regards to some key information, such as quality and reliability of services, that they can convey (Tait, 2017). In fact, in the case of irregular energy supply, households are likely to resort to 'energy stacking[10]' (Pachauri, 2011; Harris et al., 2016).

[10] In order to maximise fuel security, households will use multiple different fuel sources simultaneously and poorer households will continue using traditional fuel sources, even as incomes rise (Choumert, et al., 2017).

With particular relevance to South Africa, Harris et al. (2016, pg. 2), using a multitude of South African household datasets, examined household electricity access in impoverished rural contexts. The authors revealed that access to electricity is not the "simple, monotonic process" as the literature often assumes. In fact, they argued that household electricity connections were a dynamic process as a result of a) net connections and b) household formation and dissolution processes.

The most noted limitation with regards to the use of the MEPI is that it assigns arbitrary weights to each factor used in its calculation, deeming the results sensitive to different weights (Yeu & Koch, 2020). Likewise, implicit in the use of MEPI is the so-called 'curse of dimensionality' whereby, due to the large amount of data dimensions, the analysis of the joint metric becomes inflexible (Bensch, 2013). In contrast, uni-dimensional indicators, notably the TPT, are noted for their ease of interpretation. Survey data on household income and electricity expenditure is also readily available (Foster et al., 2000; Sovacool et al., 2012; Tait, 2017). The MEPI does, however, have advantages over the TPT. The MEPI extends beyond income and captures both issues of affordability and accessibility. Multidimensional indicators capture the multi-faceted nature of energy poverty (Day et al., 2016; Chipango, 2021). Furthermore, recent literature is beginning to highlight the importance of an energy poverty indicator that reflects particular contexts, which can be achieved when employing the MEPI (Tait, 2017; Bhattacharyya, 2012).

2.2. Factors that drive energy poverty

This section seeks to establish a nexus between the factors that influence a household's energy poverty status in developing countries. The theoretical explanation underpinning the type of energy a household uses and/or their energy poverty status is based on the assumption that household agents rationally consider their energy choices subject to a budget constraint (Ningi et al., 2020). This falls in line with the theory of household utility maximisation whereby households have certain preferences for different energy types and choose their energy sources based on their perceived utility and income limitation (Ozughalu & Ogwumike, 2012; Ouedraogo, 2013). This section elucidates the various determinants highlighted by existing literature that influence a household energy poverty status.

2.2.1. Demographic Factors and Energy Poverty

Past studies only emphasised population size as the driving factor behind energy use and energy poverty (Alemayehu, 2017). However, recent studies (Ismail & Khembo, 2015; Ozughalu &

Ogwumike, 2018; Crentsil et al., 2020) have exhibited that there are many other demographic factors that have a significant effect on determining the energy poverty status of a household. Numerous studies indicate that energy poverty afflicts rural areas more so than urban areas (Ozughalu & Ogwumike, 2018; Crentsil et al., 2020). Households residing in rural areas have often not been provided with access to essential public services (Vianello, 2016; Uhunamure et al., 2017). Therefore, **locational differences**, such as rural and urban areas and/or regions, may explain the contrast in availability, dependability and accessibility of clean, modern energy resources. There is generally an abundant amount of firewood and other traditional biomass fuels available in rural areas relative to urban or peri-urban locations, making these inefficient fuel sources a promising alternative to rural households. In a similar vein, households in rural areas are more likely to have dwelling types that reflect the poor infrastructure of overlooked regions.

The **age of the household head** can dictate whether modern energy sources are adopted by a household or not. Older individuals have reported to indicate a preference towards traditional biomass fuels for cooking and heating purposes (Menash & Adu, 2015). Using a logit model to predict the determinants of multidimensional energy poverty, Crentsil et al. (2020) find evidence that the older the age of the household head, the more likely a household is to find themselves in energy poverty. A study by Frizche (1981) identified that energy consumption takes on an inverted U-shape over a the period of child raising – this is in line with Pachauri's (2004) finding of households later on in a 'family life cycle' having an increasing per capita energy consumption.

Both gender-specific labour sharing and **female bargaining power** are said to be powerful determinants of household fuel decisions and the status of energy poverty (Ozughalu & Ogwumike, 2018). Female-headed households tend to exhibit a preference for the adoption of more modern, cleaner energy sources as opposed to male-headed households (Rahut et al., 2017; Karimu et al., 2016; Rahut et al., 2014). A study done in rural Malawi, for instance, by Dunga, Grobler & Tchereni,(2013) points to a greater likelihood of men being energy poor. Menash et al. (2015)'s analysis of Ghanian households similarly finds that male-headed households possess a higher likelihood of using traditional biomass fuels. This may be attributed to the fact that females and children are normally burdened with fuelwood harvesting, for instance, which is time-consuming and laborious; thus, they have a preference for alternative sources. Linked to this, marital status (if the household head is married) is a significant negative determinant of energy poverty in the household – perhaps because,

typically, a husband and wife would make a joint decision regarding energy sources that benefit the entire household (Abbas et al., 2021).

Conversely, some studies have pointed to results that suggest a higher likelihood for female-headed households to exist in one form of energy poverty (Annecke, 2002; Pachauri & Rao, 2013; Crentsil et al., 2019). The reason underpinning this finding may be because females are constrained to certain types of energy services due to culturally-dictated patterns of asset ownership – such assets may be essential to alleviate multidimensional poverty deprivation. They are limited to accessing inefficient, unclean sources, rendering them largely energy poor (Annecke, 2002). The sluggish transition from inefficient energy sources to modern sources may be attributed to the lack of consideration granted to gender dimensions of energy poverty (Pachauri & Rao, 2013).

Education is viewed as an essential tool in poverty reduction (Kanagwa & Nakata, 2008). Higher education levels of the household head imply enhanced knowledge and information availability to make informed decisions that stand to benefit household members. Furthermore, linked to increased knowledge and education, individuals are generally able to utilise and appreciate sophisticated energy technologies and are thus willing to transition from traditional biomass fuels to clean, modern energy sources (Uhunamure et al., 2017; Ozughalu & Ogwumike, 2018). To cement this notion, Menash & Adu (2015), using a multinomial logit model to estimate the determinants of fuel choice in Ghana, illustrated higher returns to education in household energy types. **Employment status** is similarly theorised to enable a household's use of modern energy sources (Reddy, 2004).

2.2.2. Socio-economics Factors and Energy Poverty

Revisiting the energy ladder hypothesis, the relative prices associated with different fuel types play a defining role in a household's choice of fuel, and thus energy poverty status (Crentsil et al., 2020). However, in rebuttal to this hypothesis, Masera et al.'s (2000) fuel-stacking model posits that households adopt a range of energy sources, regardless of income levels and based on preference instead, as opposed to moving up the 'energy ladder' according to income levels.

Household income is one of the major drivers of household energy poverty. Generally, lower income households find themselves in a state of energy deprivation more than higher income households (Pacuhari & Spreng, 2014; Alemayehu, 2017). According to the energy ladder hypothesis and its subsequent fuel-switching model, affordability of energy sources and income levels interact in such a way that poorer households allocate a portion of their already

limited income to unclean and cheaper biofuels as opposed to clean, modern energy sources. As a household's socio-economics standing improves, so does its access to clean, modern energy sources (Hosier & Dowd, 1987; Crentsil et al., 2020).

However, despite this resounding linkage between energy poverty and income, it has been shown that in many instances, income poverty and energy poverty may not overlap (Khandker et al., 2013). For example, in areas where wood is readily available as a free, alternative fuel source, there is no explicit opportunity cost involved and households can access it at all times (Uhunamure et al., 2017). However, there may exist implied costs related to biomass fuels, for example, in terms of time commitments and physical exertion; if supply of a biofuel resource is limited, it may also take on a cash/ bargaining value (Lloyd, 2014).

Theoretical explanations regarding household energy demand for a particular energy source posits that price, and the price of alternative sources, is an influential factor for a household's fuel choice, and thus energy poverty status (Davis et al., 2008; Menash & Adu, 2015). Interestingly, Menash & Adu (2015, pg. 1408) hypothesise LPG as a '*giffen*' good in that it seems to have a "positive own price effect". In line with this discussion, Ningi et al. (2020), using a tobit regression technique, found the **price of energy sources** to be a highly significant determinant of multi-dimensional energy poverty. In urban Ethiopia, the price of kerosene is a crucial driver behind household energy poverty (Alem & Demeke, 2020). Both income and the presence of electrical assets, such as electrical cooking appliances, are purportedly driving factors behind electricity consumption (Davis et al., 2008). The expenditure-approach to measuring energy poverty is predicated on the link between low-income status and energy deprivation (Ozghalu & Ogwumike, 2018; Pachauri & Spreng, 2004). Furthermore, the **reliability** of household energy sources also has a powerful determining effect regarding a household's energy type, especially noted for cooking purposes (Menash & Adu, 2015).

Compounding the above-mentioned household income effect , a larger **household size** can also exacerbate the status of energy deprivation if a smaller portion of fixed income and/or energy resources has to be distributed among more persons (Ningi et al., 2020). Furthermore, previous studies from Ghana have shown that the greater the household size, the less likely a household transitions from unclean energy sources to clean energy (Mensah & Adu, 2015; Karimu, 2015). Cheaper and 'unclean' fuel sources can be employed for cost-saving purposes in larger households where there may exist higher and competing energy demands for inadequate energy resources (Muller & Yan, 2018). Although larger households can potentially promise more

individuals to engage in fuelwood collection, as per the definition of MEP, these households are still considered energy poor, despite having more 'energy security'[11].

Energy policies, which are mostly subject to intervention in low- and middle-income countries, ultimately influences the price, availability and reliability of energy sources – this is an important supply-side determinant (Heltberg, 2005; Renner et al., 2019). The impact of an energy price change on a household's welfare is dependent on three factors: the scale of the price change; the relative use of energy sources in a household's energy bundle, and substitution between ability and willingness. This is not to mention the indirect effects of energy price changes on the price level of general goods and services in the economy (Renner et al., 2019). Renner et al. (2019) find that changes in energy prices have significant impacts on household energy poverty in Indonesia, whereby they use the expenditure-based definition of energy.

2.2.3. Behavioural factors and Energy Poverty

In line with the concept of fuel stacking, whereby households opt for a range of energy sources – some low-cost and some high-cost – as incomes rise, the use of certain types of fuel for particular activities is dependent on **social factors, needs and preferences**. Households adopt multiple fuel types to raise the chances of energy supply (Pachuari & Spreng, 2004). Dependence on a single fuel type is perceived to raise the household's susceptibility to fuel price shocks and thus supply variations (Zubi et al., 2019). **Fuel stacking behaviour** is demonstrated in cooking practices: a specific fuel type is used according to the quantity, desired taste and type of food being prepared. These cooking habits may have cultural dependencies (Heltberg, 2004).

There are other behavioural factors to explain the adoption of clean, modern energy sources. Olang et al. (2018)'s analysis of households in Kisumu City, Kenya, indicated that a household's energy poverty status is a function of **convenience in usage, safety perceptions and contentment** with the smell of the fumes emanating from cooking appliances. Furthermore, in India, the adoption of pro-environmental behaviour has shifted communities away from traditional cooking practices involving firewood (Herington et al., 2017). Forms of

[11] Energy security can be defined as "as the uninterrupted availability of energy sources at an affordable price." (IEA, 2021).

extrinsic incentives, such as subsidization programmes of cleaner energy sources, may further alter a household's energy poverty status (Herrington et al., 2017).

Linked with higher education levels, Uhunamure et al. (2017) exhibited that survey respondents in rural Limpopo, South Africa, were more likely to express **a positive attitude towards environmental conservation** and thus clean energy usage. In this study, preferences revolved around efficacy of sources in relation to time; food-taste and availability and accessibility of the energy source. Firewood was understood to tick all the above-mentioned preferences. Furthermore, in rural regions, often forests and grasslands are considered communal areas; therefore, traditional biomass fuels are accessible energy sources for surrounding communities to harvest (Uhunamure et al., 2017).

2.2.4. Technological Factors and Energy Poverty

One way of addressing the problem of energy poverty is by making energy technologies available to the population, specifically those deprived of clean, modern energy services. Clean energy technologies offer a solution to breaking the energy poverty cycle (Yadav et al., 2019). As implied in the Energy Ladder Hypothesis, a household should transition to cleaner energy sources as household income rises. However, this theory is premised on the assumption that there exists the ability to use and appreciate more sophisticated energy-based technologies (Ogwumike & Ozughalu, 2012). This sub-section previously touches on the supply side of modern energy sources and how this is related to energy poverty.

Household energy poverty is alleviated by access to electricity as this allows households to adopt a wider array of energy sources. (Barnes et al., 2011). However, private-owned energy utilities are deterred from serving remote, poor areas for reasons such as the loss of profit associated with expanding to such areas (Bazilian et al., 2010). Researchers have found that the expansion of **off-grid, decentralised renewable energy programs**, such as the introduction of solar photovoltaic (PV) systems, are effective in increasing access to electricity in developing countries' rural areas. Renewable energy projects further protect low-income groups from volatile fossil fuel prices, and are environmentally benign in comparison to other energy sources. Previous literature indicates that household energy poverty can be overcome through the implementation of micro-grids (Valencia et al., 2021), small-scale renewable energy projects (Terrapon-Pfaff et al., 2014) and fossil fuel subsidies (Zubi et al., 2019).

However, such programs have been unsustainable due to the lack of consideration for the cultural and political dynamics of local communities. To ensure the success of off-grid energy

programs, the voices and needs of users should be considered (Urmee & Md, 2016). These factors, amongst others, can explain the difficulties encountered in South Africa's Solar Electrification program rolled out in Limpopo and the Eastern Cape (Prasad, 2007). Nigeria is an example of a country that has an abundance of fossil and renewable energy sources, but a large prevalence of energy poverty. In order to the address this issue, policy recommendations include off-grid, decentralised energy supply solutions for households (Mshelia, 2013).

2.3. Effect of Energy Poverty on Development Outcomes

2.3.1. Theoretical foundation

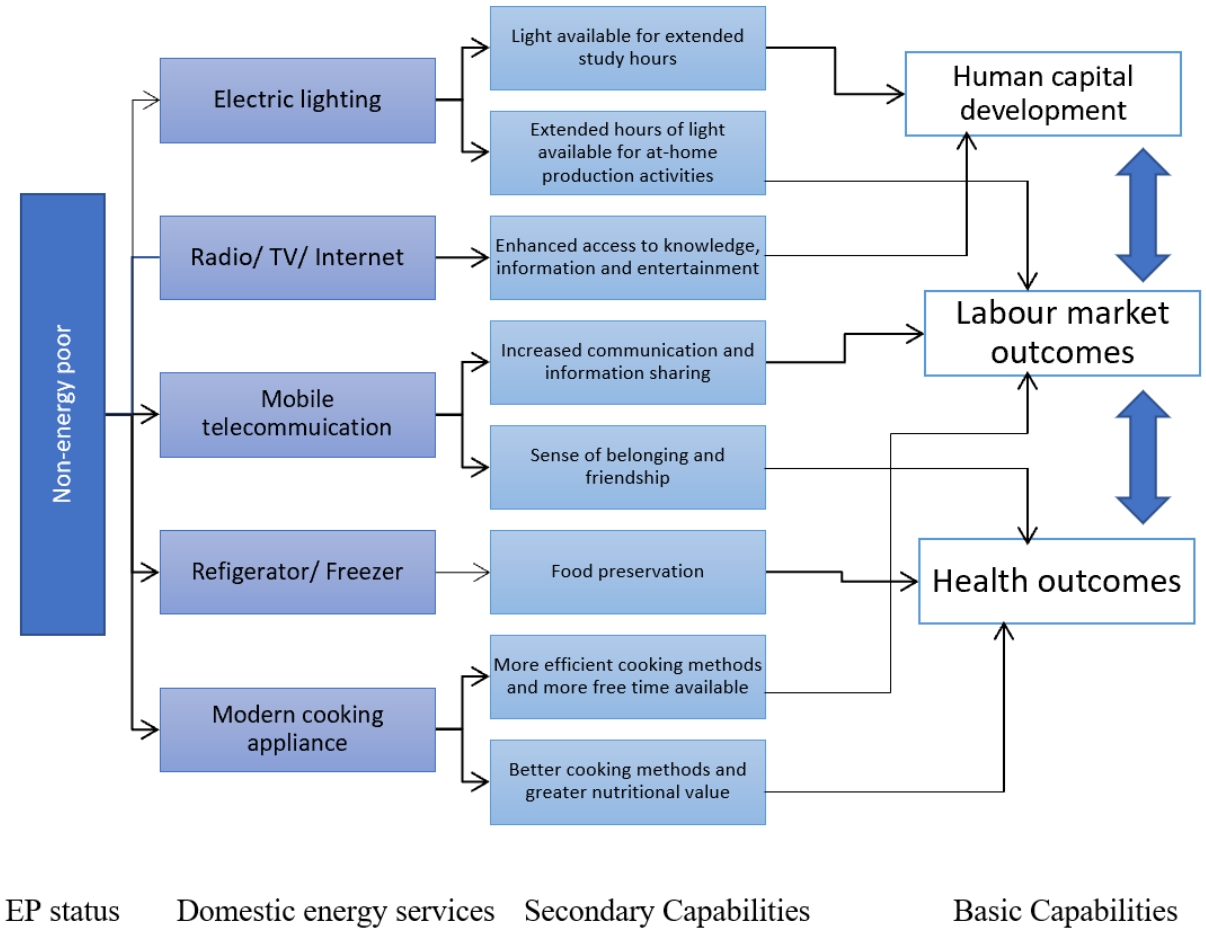
The social exclusion theory of poverty posits that poverty is akin to being rendered socially disadvantaged – i.e., unable to participate in consumption, production, political engagement and social integration – and looks at poverty in a multidimensional way (Adusah-Poku et al., 2020). In line with the sentiments expressed by Sen (1999) and Battacharyya (2012), the term *development* used for the purposes of this work will encompass aspects beyond the traditional focus on economic growth and wealth as a measure of human welfare. Instead, development is interpreted within the lens of a sustainable, socially-desirable, and environmentally-friendly framework. Recent work by Adom et al. (2021) highlights a profound connection between energy and development outcomes and, using macro-level data from Ghana, finds that energy poverty has a adverse effect on income, education and life expectancy.

According to the energy ladder hypothesis previously discussed, energy deprivation is associated with 'under-developed' nations; the level of energy poverty is likely to decrease as development occurs (Ogwumike & Ozughalu, 2015). Battacharyya's (2012) study on the link between energy access and development illuminates how better HDI scores are positively correlated with greater levels of electricity access.

The discussion below serves to cement these notions by illustrating the possible associations between energy poverty and certain development outcomes – such as human capital development and labour force participation, health status and gender-based effects. It must be noted that, there are likely to be interactions amongst various outcome indicators (Khandker et al. 2013; Ogwumuke & Ozugalu, 2015). Njiru and Letema (2018) illustrates how low electricity access causes households in the Kirinyaga district in Kenya to rely on traditional fuels, which both exposes them to health risks and has impacted their dietary patterns in an unfavourable way. Similarly, numerous studies have pointed to the general impact of energy

poverty on overall household wellbeing, which encompasses outcomes such as reduced earning capabilities, adverse health effects and lower school performance (Halkos & Gkampoura, 2021; Rafi et al., 2021; Phoumin & Kimura, 2019; Oum, 2019). Figure 2 below paints this theoretical framework by exhibiting the interactions between modern energy sources and potential development outcomes.

Figure 2 Transmission of energy benefits and pathways to development indicators



Source: Adapted from Sambodo & Novandra (2019; pg. 115) and Day et al. (2016)

It must be cautioned that the theoretical model, however, overlooks the fact that benefits of household electrification cannot be generally applied. The benefits rather depend on case-specific factors such as gender roles, the economy's labour absorptive capacity and supporting socio-economic policies (Rathi & Vermaak, 2018; Matinga & Annegarn, 2013). Matinga & Annegarn's (2013), using ethnographic grounded theory to understand the perceived impacts of modern energy in rural Eastern Cape villages, illustrate how the benefits from electrification

might not materialise and are dependent on non-energy related factors, such as gender roles, power relations, skill endowment and competing attractions

2.3.2. Labour-market and related outcomes

The 'growth hypothesis' posits that increased electricity consumption is positively correlated with GDP growth at the national level – numerous studies exist to support this claim (Khanna & Rao, 2009; Payne, 2010). Looking at the effects of cleaner and modern energy resources on labour market outcomes, there are a number of mechanisms at play. Firstly, there is a time-saving dimension involved, especially for women and girls, when transitioning from solid, traditional fuels to electric lighting and cooking. Effectively, efficient modern energy sources allow women to engage less in previously time-consuming activities, such as food preparation. With less time allocated to home based activities, women are therefore more likely to participate in the labour market. Electricity connections in rural areas may have the additional effect of lowering the costs associated with producing goods and services at home, effectively allowing individuals to engage in entrepreneurial endeavours (Dinkelman, 2011).

The technology shock of electricity and/ or modern, clean energy resources on labour supply is, however, reportedly ambiguous (Becker, 1965). This is because electricity/ modern energy may increase the length of a productive day, resulting in a greater demand for normal goods and thus an increase in labour supply to meet this demand. However, counter-acting this effect, households may allocate freed up time, as a consequence of time-saving technologies, such as electricity connection, towards home-based activities. Another channel through which energy poverty may affect an individual's welfare is through their behaviour, such as rendering more susceptible to cognitive biases in decision-making (DellaValle, 2019) and dampening their cognitive functioning (Cede˜no Laurent et al., 2018), thus reducing their ability to participate in the labour market.

A large body of literature examines the effects of household electrification on labour force outcomes. A recent study done by Rathi & Vermaak (2018) estimates the effect of rural electrification, at the household level, on labour marker outcomes in South Africa and India using two techniques: propensity score matching methods and panel fixed effects estimation. Their findings suggest that the benefits of rural electrification include increased annual incomes earned by individuals in paid employed. Similarly, with respect to South Africa, Dinkelman (2011) illustrated that approximately 15,000 more women were engaged in employment due to rural electrification in the Kwa-Zulu Natal province. On the other hand, a study done in China

shows that being energy poor, according to the TPT, can increase an individual's entrepreneurship propensity. This may be because negative personal circumstances necessitate traits essential for becoming an entrepreneur, such as self-reliance and resourcefulness (Cheng et al., 2021).

2.3.3. Health outcomes

An abundance of prior literature addresses the effect of energy poverty on health outcomes; evidence suggests that ill-health is associated with inaccessible and unaffordable energy sources (Gonzalez, 2016; Zang et al., 2019; Zhang et al., 2021). Energy poverty has been shown to have a detrimental effect on public health on a macro-scale (Pan et al., 2021) and increase household health expenditures (Bukari et al., 2021). Furthermore, studies point out that the health impacts of energy poverty are more severe among children than adults (Thomson et al., 2003).

There are multiple channels through which energy poverty has an effect on an individual's health. In the global South, where temperatures can average 46 degrees Celsius annually, individuals residing in households lacking adequate thermal regulation and ventilation are forced to open windows and cook indoors. This can result in vulnerability to crime and indoor pollution respectively, therefore posing the risk of increasing anxiety and mental instability (Sovacool et al., 2012; Lin & Okyere, 2020). Hailmariam et al. (2021) showed that energy poverty is able to increase the likelihood of physical violence amongst Australian households. The lack of adequate heating in colder months can also be a major contributor to ill-health, and even increased rate of mortality (Healy, 2003).

Secondly, the usage of certain fuels, such as biomass fuels and paraffin, for indoor cooking and heating can lead to indoor air pollution, which is the primary cause of respiratory ailments (Muller et al., 2003). Indoor air pollution is responsible for various diseases found in many households such as acute respiratory infection, otitis media, lung cancer, chronic obstructive pulmonary disease, asthma, cancer of the nasopharynx, laryngeal cancer, low birth weight, tuberculosis, perinatal conditions, cataract and blindness (Kimemia et al. 2014). The negative effects by means of such energy resources is compounded by poor ventilation in low-income dwellings and especially for women, children and the elderly, who spend most of their time indoors (Gonzales-Eguino, 2015). According to the American Thoracic Society (2018), burning of biofuels indoors generates air pollutants, such as soot, nitrogen dioxide and particulate matter, which, upon regular inhalation, can lead to a range of lung ailments – the

most common being chronic bronchitis in adults and pneumonia, which adversely affects lung growth and development, in children[12]. Unreliable and unsafe energy sources also provide risks of burns, fires and electric shocks. Worldwide, fire-related burns, mostly assumed to be cooking-related, are responsible for roughly 265,000 deaths annually (USAID, 2017).

Recent literature has also focused on the effects of energy poverty on mental health. In developing countries, mostly women face the added burden of collecting wood for fuel purposes and are subject to physical strain (Reddy et al., 2000). Furthermore, in humid and hot countries, energy poor households tend to cope with heat stresses by opening windows, which makes them feel vulnerable to crime and violence (Spengler et al., 2012). Conversely, a household's inability to generate heat also contributes to declines in mental health (Pevalin et al., 2017)). However, despite the growing interest and identified importance of mental health outcomes as a limiting factor to capability, there has been scarce documentation on how energy poverty could affect wellbeing in this regard – especially in developing countries (Churchill & Smyth, 2020). One study isolating the causal association between energy poverty and mental health was conducted by Lin & Okyere (2020). The authors indicated that increased energy poverty, using a multidimensional index, was associated with a 1.9 fold in severe depressive symptoms amongst households in Ghana. Zhang et al. (2021) similarly exposed the effect of multidimensional energy poverty on both physical and mental health amongst household in China. Their findings exhibited that the mental health status amongst urban households decreased due to energy poverty, but amongst rural households, physical health deteriorated as a result of energy deprivation. However, it must be noted that the magnitude and direction of energy poverty's affect can differ across individuals with varying risks of depression (Zhang et al., 2022). Meanwhile, Nie et al. (2021), looking at the China Family Panel Studies, showed energy poverty had a pronounced adverse effect on the life satisfaction levels of males and those residing in central regions. Delugas & Brau (2021) cements this notion by illuminating the relationship between multidimensional energy poverty and life satisfaction: the magnitude and significance of the coefficient attached to life satisfaction rises as MEPI rises.

Lastly, households may reallocate spending towards energy expenditures and away from food and non-food expenses (Sola et al., 2016). For instance, Sambodo & Novandra (2019) illustrated that energy deprived households are estimated to allocate a larger proportion of their

[12] Other lung ailments include asthma, tuberculosis, interstitial lung diseases, heart disease, and lung cancer (American Thoracic Society, 2018).

income on food and non-food items – this was especially the case where households lacked modern cooking facilities. Their results hinted a greater incidence of malnourishment associated with lack of electricity access. This was result was cemented by Rafi et al.'s (2021) study of energy poverty on child health and human capital development and Fay et al.'s (2005) study of the role of infrastructure, such as grid electricity access, on child anthropometric measures. In contrast, a study in Australia is indicative that energy poverty is positively associated with obesity – this association can occur through channels such as sleep or general and mental health (Prakash & Munyanyi, 2021).

2.3.4. Human capital development and child education outcomes

Previous literature documents the nexus between decreased energy poverty (alternatively, increased access to the electricity grid) and improved education-related, both short-term and long-term, outcomes amongst school-aged children (Banjeree et al., 2021). It is necessary to differentiate between short-term outcomes (absenteeism) versus long-term (educational attainment). Short-term education outcomes, which can be attributed to household energy poverty as per the discussion below, may be a strong predictor of later school performance and attainment (Liu et al., 2021). Oum's (2019) study includes a lagged energy poverty variable to estimate the effect of a household's mean education years in Lao, and proves that the effect is negative and statistically significant.

Karim et al. (2018) exploits nationally representative household data from Ghana to estimate the effect of energy poverty indexes – by cooking and lighting access – on the number of classes missed by a child. Their results indicate that energy poverty increases the number of classes a child will miss. Other studies similarly show how access to clean and efficient energy at a household level can enhance a number of education outcomes – namely basic literacy (IEA, 2009); school enrolment (Khandker et al., 2013); education attainment (Kumar and Rauniyar, 2011) and test scores (Rafi et al., 2018). Dasso et al. (2015) provides contrary evidence in that household electrification may not translate into a child's increased willingness to go to school.

There are two main, interconnected pathways through which energy poverty can affect education in the short-term: Firstly, children in households deprived of modern, efficient energy sources tend to spend more time collecting firewood as opposed to allocating time to school and studying (Sovacool & Drupady, 2012), and this is thought to hold more true for school-going girls (Heltberg, 2005). However, some studies have indicated that the opposite effect can hold whereby the education of males benefit more from energy poverty (Karimu et

al., 2018). Secondly, increased study times can be attributed to access to better-quality lighting and for extended hours past daylight (Khandker et al., 2012). Effectively, enhanced access to modern energy sources can increase the hours dedicated to study through better lighting and decreased household duties, which can increase school attendance.

2.3.5. The effect of energy poverty on gender-dimensions

Access to affordable, clean and modern energy resources includes a gender dimension in that it can contribute to women's economic empowerment (Chipango, 2021; Das et al., 2020; Grogan, 2016). Generally, women allocate up to three times more effort and time towards household chores and care-taking duties than their male counterparts (UN, 2019). Gender benefits from clean, modern energy access can manifest in various forms – such as decreased fertility rates, increased work hours and greater leisure time (Grogan, 2016).

As discussed in previous paragraphs, women are the most susceptible to the adverse health-effects that unclean energy resources present (Das et al., 2020). For instance, Abbas et al. (2021), employing a structural equation modelling technique, predict a statistically negative causal relation between MEPI and health risks for women in 11 developing countries in Asia. Furthermore, electrification and modern energy access also include a time-component: it may relieve women of burdensome household chores and free-up hours to allocate to home-based production activities and/or employment propensities (Grogan, 2016). In Rathi & Vermaak's (2018) study on household electrification in rural areas in South Africa, the labour market benefit solely came from the increased earnings for women who worked versus their male counterparts. Dinkelman (2011) and Grogan & Sadanand (2013) both establish positive effects of rural electrification on women's labour force participation outcomes in South Africa and Nicaragua respectively. These results can be attributed to the increased use of time-saving technologies, which can make available more productive hours to be allocated to income-generating activities.

Furthermore, the combined effect of available communication/ entertainment resources and labour-saving technologies translates into more women being able to use their available leisure time on television/ radio for educational purposes. Women may learn about contraception and/or abstinence, resulting in reduced sexual contact and thus lower fertility rates (Grogan, 2016; La Ferrara et al, 2012). Of course, this effect can operate in the other direction whereby greater leisure time and increased income, assuming income is correlated with electrification results in reduced fertility rates.

However, the way in which women utilise time is dictated by social contexts and perceptions, thus curbing their employment potential. For instance, Chipango (2021) discovered that, despite electrification, women in Zimbabwean villages are still expected to use firewood for cooking purposes as imposed by the cultural expectation on women to be the 'meal-providers'. Additionally, numerous authors warn researchers against oversimplifying the gender-energy nexus (Chipango, 2021; Das et al., 2020; Listo, 2018). In energy poverty literature, it is necessary to debunk the 'gender myth' that women are a homogenous, vulnerable. Race, class, ethnicity and other socio-economic factors often alter the experiences that women face (Listo, 2018; Lamb, 2019). The benefits from electrification programmes/ energy poverty interventions are not experienced uniformly by everyone in a community (Matinga & Annegarn, 2013). Listo (2018) finds that often development literature resorts to the conclusion that "*energy saves, modernises and empowers women'* without due consideration for the way energy alters power dynamics within social and institutional structures (Listo, 2018, pg. 13). It is therefore essential that academic studies and policy engage with the various realities women occupy and avoid rendering them as vulnerable, submissive individuals.

2.3.6. Energy Poverty in the South African context

To date, there is limited information on the effects of energy poverty on development outcomes in South Africa. However, there are several studies analysing the existence of energy poverty in the country. Bohlmann & Inglesi-Lotz (2018) exhibit that, despite widespread electricity provision and the existence of FBE, low-income households still opt to use a profile of energy sources, such as wood and paraffin: roughly 70% of households in South Africa spend on energy sources besides electricity. It is important to understand the energy consumption behaviours of low-income households in order to inform a holistic picture of energy poverty (Israel-Akinbo et al. 2018).

Using the first four waves of the NIDS dataset, Israel-Akinbo et al. (2018) employ the MEPI metric to the South African context. They find a startling result: the percentages of low-income households that are energy deprived in urban areas increase after 2010, whilst energy poverty rates decrease in rural areas for lower income households (Israel-Akinbo et al., 2018). Another study by Le Roux and Choumert-Nkolo (2021) found that multi-dimensional energy poverty had decreased by approximately 20 percentage points between 2008 and 2017. Rural-urban migration was a factor contributing to additional reductions in energy poverty. An advantage of the MEPI approach, versus previous methods utilized in South African energy poverty

literature, is that it is decomposable: useful energy needs at several demand sectors of households may be directly measured (Israel-Akinbo et al., 2018; Nussbaumer et al., 2012).

The most indigent households in South African urban townships make use of a *mbaula* – which is described as "a metal drum with a simple grid to support the coal, and holes in the side of the drum to admit air" (Lloyd, 2014: 3). This energy technology, when lit indoors, leads to air conditions which may result in fatal levels of carbon oxide (Lloyd, 2014; WHO, 2010). Families will often invest in cast-iron stoves when they can afford to; however, these too represent their own problems, such as smoke pollution (Lloyd, 2014). Both Makonese et al. (2020) and Lloyd (2014) point to paraffin as the fuel of choice for households in township areas – this is because it use for 'wick stoves' permits simmering and it can be readily traded. However, it is not without its problems; 'shack fires' often arise because of uncontrolled paraffin use for wick stoves. Furthermore, Lloyd's (2014) and Makonese et al.'s (2020) discussions emphasise how both LPG and electricity sources have seen a slow up-take amongst low-income households.

Similarly, Israel-Akinbo et al. (2018), using wave 1 from the NIDS dataset, indicated how low-income households alter their energy source used for cooking as income increases. However, energy stacking behaviour does persist; although, despite having access to electricity, some households still live in energy poverty. Likewise, households residing in Gauteng's informal urban settlements were shown to use multiple fuels – i.e.) *fuel stacking* – as this allows for several different cooking fuels in a cheap and affordable way (Makonese et al., 2020). This discussion illuminates how households transition from one energy source upon increased income; however, there also seems to be a degree of 'stickiness' due to preferences for one fuel source over another.

As per the discussion in Chapter 1 on South Africa's energy policies, it is evident that the South African government has directed efforts to enable electricity usage amongst impoverished households in order to promote pro-poor development. Over the years, numerous authors have sought to establish the impacts stemming from South Africa's energy policies on household welfare. The seminal paper by Davis et al. (2008) analyses whether the introduction of the FBE in 2003 had a positive effect on a household's electricity consumption and energy profile. Their findings, based on panel data from two rural areas, point to the apparent increase in electricity demand amongst low-income households due to FBE. This was further cemented by Prasad and Visagie's (2006) study. Another energy-targeted approach made by the government was the implementation of SHS in rural households (Prasad & Visagie, 2006). The impacts of these

SHSs on households in the Limpopo province included SHS-owners purchasing less fuel, money-saving behaviours, radio and television entertainment and brighter lights (Prasad & Visagie, 2006). Furthermore, Azimoh et al. (2015) established that, holding all else constant, households that lacked SHSs still relied heavily on dirty, inefficient energy sources such as paraffins, candles and fuelwood. The SHS also showed to have positive influences on a household's skill acquisition and children's education; although, there were numerous problems reported with the system (such as SHS's inability to meet a household's energy needs and theft of the solar panels).

Despite these policy attempts, recent literature has shown that the percentage of households in energy poverty, according to the MEPI approach, is growing in low-income, urban households. A driving force behind the persistence of MEPI could be due to the unaffordability of modern heating sources (Israel-Akinbo et al., 2018). Using the first four waves of the NIDS dataset, Israel-Akinbo et al. (2018) showed that approximately 95% of both rural and urban low-income households are deprived of a heating source, whilst the percentage remains at 65% with regards to lighting. At an aggregate level, energy sources, such as electricity coal, diesel and gasoline, have an 'income-enhancing effect' in South Africa, resulting in increased between-group inequality relative to per capita income (Ngepah, 2011). This finding points to the need to target certain energy sources in order to reduce inequality.

Chapter 3. Data Description

This chapter is intended to illustrate the make-up of the dataset used for the purpose of this study. The chapter is organised to serve a two-fold purpose. Firstly, the dataset is presented, and the method of data collection is described. Secondly, a data analysis section is included to provide an insight into the key variables and their summary statistics. This section will elucidate preliminary associations between household energy poverty, with a specific focus on the MEPI, and individual development indicators.

3.1. Presenting the data source: The National Income Dynamics Study (NIDS)

In this study, I utilise all five survey waves of the South African National Income Dynamics (NIDS) dataset that was implemented by the Southern Africa Labour and Development Research Unit (SALDRU). NIDS is a longitudinal dataset which was collected over a ten-year period: 2008 (wave 1); 2010 to 2011 (wave 2); 2012 (wave 3); 2015 to 2016 (wave 4) and 2017 (wave 5) (SALDRU, 2018).

The data collection process took place as follows: A stratified, two-stage cluster sample design was used to sample households in the baseline year (2008). A nationally representative baseline sample of 28,000 individuals residing in approximately 7,300 households was collected (Leibbrandt et al., 2009). This baseline sample consisted of 400 Primary Sampling Units (PSUs) that was extracted from Statistic South Africa's (StatsSA) 2003 Master sample, whereby there was a further target of 24 households per PSU (Leibbrandt et al., 2009b). The realised 28,000 individuals from wave 1 formed the Continuing Sample Members (CSMs) for the following waves. In instances where babies were born to CSM women, they also became a CSM. From wave 2 onwards, co-residents became Temporary Sample Members (TSMs) and were also interviewed (Brophy et al., 2018). Survey questionnaires consisted of households, all CSM and TSM adults (ages greater than 15) and children (ages less than and equal to 15), whereby a caregiver would answer the questions on the child's behalf. To maintain the sample's representativeness, Wave 5 (2017) included a top-up sample because of the high-rates of attrition amongst certain race groups (White and Indian/Asian) and high-income respondents (Brophy et al., 2018).

In order to create a panel dataset, the survey reinterviewed the CSMs, and any TSMs, by tracking individuals across the waves according to a unique identification number (*pid*). Likewise, each household is given a unique identifier (*hhid*) (Brophy at al., 2018). All five waves of the dataset were merged to create a panel of 15,703 individuals and 24,609 households – this consists of those individuals who were successfully reinterviewed in all five waves. For the purpose of this study, a panel dataset, such as NIDS, is preferred over other household surveys, such as the General Household Survey (GHS), as it allows one to track the same individuals over time and thus account of time-invariant individual features (Woolridge, 2012). In line with the caution raised by Finn and Leibbrandt (2013), I refrain from calling the panel nationally representative[13]. Furthermore, numerous technical sources highlight the need to correct for any biases that may result from non-random attrition between wave 1 and the subsequent waves (Brophy et al., 2018; Branson & Wittenberg, 2011). Therefore, to ensure comparability over time, I employ panel weights available in the dataset.[14] To ensure the appropriate standard errors of variables, the complex survey design elements, such as NIDS's stratification at the district council level and clustering at the cluster level, are taken into account (Branson & Wittenberg, 2011).

The main objective of the survey was to collect data on poverty and well-being in South Africa over time (Brophy et al., 2018); however, the dataset is also rich in information on expenditure, employment, labour market participation, health, education and household well-being. The last variables are the most crucial data collected within this survey as it pertains to variables relating to energy expenditure, access to energy sources and asset ownership – all of which are invaluable in the construction of energy poverty indicators exhibited below (SALDRU, 2018; Israel-Akinbo et al., 2018; Nussbaumer et al., 2012a). The availability of NIDS represents an unprecedented opportunity to examine the impact of energy poverty and its effects on an individual's welfare in three domains – namely, health, labour market outcomes and education – as studies have not yet embraced this topic in post-Apartheid South Africa. In sum, since the NIDS dataset covers the necessary variables related to energy poverty indicators and outcomes associated with development indicators, it will be incredibly useful for the purpose of this investigation.

[13] Finn & Leibbrandt (2013: pg. 5) note that one is unable to interpret the sample as nationally representative if the waves were merged as independent cross-sections.
[14] It must be noted that there exists no panel weight for wave 1 observations. To correct for this, the only plausible strategy was to employ the wave 5 panel weights and use these as the weights for individuals.

Table 1 Key variables used and their definitionsbelow is used to highlight the key variables, and their definitions, employed based on the literature overview in Chapter 2. In the proceeding subsections, I will outline the derivation of the chosen energy poverty indicators and provide a preliminary analysis of the key variables.

Table 1 Key variables used and their definitions

Term	Definition
Energy Poverty Indicators	
Multidimensional Energy Poverty Indicator (MEPI)	A household is considered energy poor (=1) if the weighted sum of household energy deprivations is greater or equal to 0.33, and 0 otherwise.
Energy-expenditure ten-percent threshold indicator (TPT)	A household that spends more than 10% of their net income on energy is regarded as energy poor or in energy poverty (DoE, 2013; pg. 11)
Labour market measures for working age population (ages 16 – 64)	
Strict unemployment	Binary variable: =1 if an adult individual is currently not employed and have actively searched for employment in the past four weeks but did not work during seven days prior to the interview despite being available and wanting to work (StatsSA, 2002).
Broad unemployment:	Binary variable: =1 if an adult individual is currently not employed but they would have liked to have worked in the last four weeks, despite not taken active steps to find work (StatsSA, 2002)
Labour force participant:	Binary variable: =1 if an individual, at the time of the interview, reported working for pay, being unemployed but looking for work or discouraged from seeking work; =0 if the individual was not economically active over the last four weeks (StatsSA, 2002).
Adult Health Outcomes (age > 15)	
Life satisfaction	Ordinal scale: 1 pertains to being very dissatisfied and 10 pertains to being very satisfied
Depressed	Binary variable: =1 if CES-D score is greater or equal to 12, 0 otherwise
Overweight	Binary variable: =1 if Body Mass Index (BMI) greater than 25, 0 otherwise
Objective health index	Health index capturing the number of affirmative (=1 for yes) responses to questions pertaining to the presence of a bad health condition in the last 30 days. The health conditions include: fever, persistent cough, cough with blood, body ache, headache, back ache, joint pain, diarrhoea, painful urination, swelling of ankles and severe weight loss.
Anthropometric measures for children (ages < = 15)	
Stunted	Height-for-age Z-score (HAZ) is less than two standard deviations (SD) below the median of WHO's health reference population (WHO, 2010; pg. 10).
Child education-related outcomes (ages <= 15)	
Education years	Number of schooling years completed.
School day missed	The number of school days missed in the last 30 days.
Individual-level covariates	
Age	Number of years old
Age-squared	Square of number of years old
Gender	Binary variable: =1 if Female, 0 otherwise
Mother's education	For children aged <= 15, number of years of education the mother has received
Mother's employment status	For children aged <= 15, binary variable =1 if the mother is employed, 0 otherwise
Education	For adults aged > 15, number of years of education completed
Marital status	For adults aged > 15, =1 if married, 0 otherwise
Smoke	Binary variable: =1 if respondent smokes frequently, 0 otherwise
Race	Categorical variable: =1 if African, =2 if Coloured, =3 if Indian/Asian; =4 if White
Household-level covariates	
Household size	Number of members residing in household.

Dependents in household	Binary variable: =1 if the there are any dependents (aged < 16 or aged > 65) in the household, 0 otherwise.
Household dwelling type	Binary variable: = 1 if informal dwelling; 0 otherwise.
Area type	Binary variable: = 1 if located in urban area, =0 if located in rural area.
Adequate water access	Binary variable: =1 if household has access to piped water, 0 otherwise
Household Income	Household monthly income (ZAR)

Notes: Although acknowledged that the usual school-going age of children in South Africa is aged six to eighteen, I restrict the analysis to the ages of children used NIDS' 'Child Questionnaire' (SALDRU, 2008). This is because the Child Questionnaire provides questions specific to schooling-related outcomes, whereas the Adult Questionnaire does not.

3.2. Data Analysis: Choice of indicator

As presented in Chapter 2 in the literature review, there are numerous approaches used in deriving energy poverty indicators – despite this, there is still an absence of consensus in the academic and policy arenas[15]. The challenge at hand is to employ an energy poverty indicator that is both sensitive to a country's context and captures all the necessary elements of energy poverty. For reasons elaborated below, I will utilise two energy poverty indicators for the purpose of this study – namely, the energy-expenditure ten-percent threshold indicator (from hereon, TPT) and the multi-dimensional energy poverty index (MEPI).

3.2.1. Energy-expenditure ten-percent threshold indicator (TPT)

The first approach to defining an energy poverty indicator looks at affordability and the inability to pay for energy services. This takes the form of energy expenditure as a proportion of total household income/ expenditure: if a household spends more than 10% of their net income on energy expenditures, they are deemed to be energy poor (Boardman, 1991; DoE, 2013). This approach was first advocated by Boardman (1991) and has since been considered the universal metric of energy poverty due to its ease of use and interpretation (Ismail & Khembo, 2015). The TPT has previously been endorsed by South Africa's Department of Energy (DoE, 2013; 2019). Therefore, in order to align, and subsequently compare, with previous policy interpretations of energy poverty, I will also adopt the TPT.

The TPT was first calculated by dividing total household expenditure on electricity and other energy sources[16] by monthly household income (Boardman, 1991; Thomson et al., 2017). All expenditure and income values are price-adjusted for inflation to reflect 2017 nominal prices.

[15] Although briefly discussed in Chapter 2.2, the full extent of this discussion in beyond the scope of this paper. Review Day et al. (2016) and Pachauri (2011) for a comprehensive discussion on the various types of approaches.
[16] Energy sources include electricity; wood; paraffin; charcoal/coal; candles; gas; purchasing/charging batteries and diesel oil for generators (SALDRUe, 2017).

One should note that household information on income and expenditure is often either not collected or is unreliable as survey respondents are hesitant to disclose their incomes (Barnes & Samad, 2018) The first step to calculating the TPT is shown by equation (3.1) below:

$$Energy\ expenditure - household\ income\ ratio = \sum_{i=1}^{n} \frac{E_i}{I_i} \quad (3.1)$$

,where E_i is the expenditure on energy sources[17] for the past 30 days and I_i is the net income of household-i.. N is the total sample population of households. Subsequently, a binary indicator can be created to distinguish between energy poor and non-energy poor households whereby an energy poor household assumes the value of 1 if the household allocates more than 10% of its net income on energy sources, and 0 otherwise. This relationship is defined in equation (3.2) below:

$$TPT_{\mathrm{i}} = \frac{1}{n}\sum_{i=1}^{n}(\frac{E_i}{I_i} > 0.1) \quad (3.2)$$

In creating the TPT indicator, I relied on variables pertaining to monthly household income and household energy expenditure. I therefore relied on NIDS' *hhincome* variable which is one of NIDS' derived variables The energy expenditure variable was calculated by summing the household's expenditure on electricity and other energy sources in the last 30 days. Data diagnostics for income and energy expenditure-related data are shown in Table 2 below.

Table 2 Diagnostics of missing data on TPT indicator variables for entire NIDS dataset

	Household income	**Expenditure on energy sources**	**Expenditure on electricity**
Any missing	-	-	-
All zero	6	2,632	1,262
Non-zero	25,571	22,945	24,315
Total (Sum)	25,577	25,577	25,577

Note: Unit of analysis at household level.

The breakdown of the TPT indicator according to a subset of variables is shown in Table 3 below. The findings suggest that there has been an increase of the proportion of energy poor households between wave 1 and wave 3 (2 percentage points), and then a decline of roughly 4 percentage points in wave 5. This change between waves 1 and 3 can be attributed to the electricity price restructuring whereby there has been an approximate increase of 33% in real

average electricity prices from 2008 until 2018 (DoE, 2018). A decrease in household energy expenditure, as seen in Wave 5, may be due to increased access to electricity in combination with effective use of the Free Basic Energy (FBE) policy or a transition away from expensive traditional energy fuels. What is interesting is the stark increase in the proportion of energy poor households that fall into the 2nd per capita income quintile. One potential explanation looks at the 2008 Electricity Pricing Policy and its introduction of an Inclining Block Tariff (IBT) structure for all billed consumers. The IBT penalised higher electricity users, such as those with medium living standards that still lack energy-saving technologies (DoE, 2013; pg. 78). This ties in with the Bohlam & Inglesi-Lots' (2018) finding that as income increases, households rely increasingly more on electrical appliances, but low-income households cannot afford energy-efficient technologies.

I now consider the proportion of households in energy poverty, according to the TPT, by area type and province. There is not a substantial difference between energy poverty rates in rural and urban areas. Despite the high prevalence of lower incomes in South Africa's rural areas (StatsSA, 2019), rural households typically rely on traditional fuel sources, such as wood and paraffin for cooking and lighting respectively, as they still might not be able to afford electricity despite the FBE (Thom, 2000; Ismail & Khembo, 2015; Crentsil et al., 2020). However, modern fuels are more cost efficient compared to traditional fuels used for the same end-uses (Barnes et al., 2005). This may account for the relatively high proportion of rural households in energy poverty compared. Over a ten-year period, the proportion of households in energy poverty across the provinces generally decrease. Households residing in the Western Cape and Gauteng are less likely to be energy poor compared to households in Mpumalanga, Limpopo and the Eastern Cape. The relatively high energy poverty rates in Limpopo and Mpumalanga can be due to households' relatively high electricity usage and use of candles and firewood, as noted by the DoE (2013). Households in Gauteng and the Western Cape mainly use electricity as the dominant energy source (DoE, 2013). According to StatsSA (2015), average household income these two provinces are greater relative to other provinces. Therefore, households in Gauteng and the Western Cape are likely to allocate smaller shares of their net income to energy expenditures.

Table 3 TPT-indicator by income quintile and location

	Proportion of households energy poor according to TPT (%)					
	Wave 1	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**	**All waves**
All	11.52	14.53	13.01	10.84	8.92	11.39
Per Capita Household Income Quintile						
1st quintile	26.24	32.32	35.85	32.29	36.28	31.18
2nd quintile	6.94	10.65	17.82	17.11	15.16	14.11
3rd quintile	6.77	5.62	5.14	8.68	9.62	7.46
4th quintile	2.14	3.55	2.91	4.07	4.13	3.60
5th quintile	1.18	4.11	5.40	1.89	00.98	2.50
Area type						
Rural	12.22	16.72	13.42	14.28	10.92	12.38
Urban	9.54	13.24	12.70	8.82	8.49	10.61
Province						
Western Cape	13.34	13.89	14.29	9.27	9.18	11.58
Eastern Cape	15.02	14.01	21.42	11.50	8.75	13.73
Northern Cape	13.44	14.67	11.48	7.23	13.31	11.76
Free State	13.29	17.29	13.21	9.31	8.43	11.72
KwaZulu-Natal	15.53	15.92	12.56	13.69	10.44	13.16
North West	11.35	15.20	10.53	12.07	12.17	12.18
Gauteng	12.55	12.62	13.67	8.20	8.97	10.87
Mpumalanga	18.02	14.37	13.82	11.61	11.20	13.35
Limpopo	16.17	17.07	14.75	13.79	11.79	14.35

Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

Notes: Analysis at the household level. Panel weights were applied to the estimates and complex survey design elements were accounted for

3.2.2. Multidimensional Energy Poverty Indicator (MEPI)

In line with the reasoning of prior research (Zhang et al. 2019; Lin & Okyere, 2020; Le Roux & Choumert-Nkolo, 2021) the concept of energy poverty in developing countries must incorporate a framework that addresses inaccessibility of modern energy services, and involves a host of economic, infrastructural, social equity, education and health concerns (Nussbaumer et al., 2012a). Based on the work of Nussbaumer et al. (2012), I utilise a similar MEPI that is composed of a weighted sum of five dimensions pertaining to six energy-related indicators, as indicated in Table 4 below. The MEPI is premised on Alkire and Foster's (2011) seminal work on the multidimensional poverty indicator and is underpinned by sentiments espoused by Sen (1976). The MEPI captures both the intensity (extent of impoverishment) and incidence of energy poverty (number of energy poor).

Table 4 Formulation of MEPI variable and weights

Dimension	Indicator (weight)	Variables	Energy poor if…
Cooking	Modern fuel (0.2)	Type of cooking fuel	Primary source of cooking fuel is biomass
	Indoor pollution (0.2)	Type of stove used for cooking	Stove is not electric or gas
Lighting	Electricity access (0.2)	Household is connected to national grid	False
Ownership of asset	Household appliance ownership (0.133)	Has freezer / fridge	False
	Ownership of entertainment or education appliance (0.133)	Has radio / television / computer	False
Telecommunications	Means of telecommunication (0.133)	Has mobile phone	False

Note: *The MEPI variable is constructed at the household level as many of the variables relating to energy access are at the household level. I use variables available in NIDS that are as synonymous with those used by Nussbaumer et al. (2012) as possible. However, NIDS does not include an explicit variable relating to 'indoor pollution', so instead I use the type of stove used as a proxy, assuming that gas and electric stoves produce less pollution than alternatives, for instance, wood fires. Furthermore, I include 'computer' under the entertainment/ education appliance indicator. The weights employed are compatible with the previous studies by Nussbaumer et al. (2012) and Le Roux & Chourmet-Nkolo (2021).*

Source: Adapted from Nussbaumer et al. (2012) and Le Roux & Chourmet-Nkolo (2021). Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017)

The reason for the choice of this indicator is three-fold. Firstly, the indicator illustrates the multi-faceted nature of deprivation with regards to energy services, and although it does not capture affordability explicitly, the use of certain energy sources and electrical appliances is indirectly suggesting affordability issues and the ability to use an energy service respectively (Nussbaumer et al., 2012; Le Roux & Chourmet-Nkolo, 2021). It has the advantage of uncovering both multidimensionality and intensity compared to unidimensional measures, such as the TPT (Abbas et al., 2021). Furthermore, the MEPI has been used in numerous reputable papers[18], indicating its degree of robustness, and it allows for a point of comparison between this analysis and pre-existing literature. Lastly, the data employed in the construction of the

[18] Studies include, but are not limited to: Nussbaumer et al., 2012; Okushima, 2017; Sadath & Acharya, 2017; Israel-Akinbo et al., 2018; Zhang et al., 2019; Lin & Okyere, 2020; Zhang et al., 2021.

MEPI[19] is available in household surveys and typically of a good quality, with regards to missing data points and outliers, relative to expenditure and income-related variables (Le Roux & Chourmet-Nkolo, 2021).

The index is constructed as follows. Each deprivation indicator (X_d) represents a basic energy service that allows for a household to live in a comfortable manner daily and assumes a value of 1 if a household is considered deprived in that dimension (Nussbaumer et al., 2012). The methodology then includes a weighting (w_d) of the indicators to reflect the respective significance of their contribution to energy poverty at the household level, as indicated in

Table 4 Formulation of MEPI variable and weights

Dimension	Indicator (weight)	Variables	Energy poor if…
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	Indoor pollution (0.2)	Type of stove used for cooking	Stove is not electric or gas
Lighting	Electricity access (0.2)	Household is connected to national grid	False
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	Ownership of entertainment or education appliance (0.133)	Has radio / television / computer	False
Telecommunications	Means of telecommunication (0.133)	Has mobile phone	False

Note: *The MEPI variable is constructed at the household level as many of the variables relating to energy access are at the household level. I use variables available in NIDS that are as synonymous with those used by Nussbaumer et al. (2012) as possible. However, NIDS does not include an explicit variable relating to 'indoor pollution', so instead I use the type of stove used as a proxy, assuming that gas and electric stoves produce less pollution than alternatives, for instance, wood fires. Furthermore, I include 'computer' under the entertainment/ education appliance indicator. The weights employed are compatible with the previous studies by Nussbaumer et al. (2012) and Le Roux & Chourmet-Nkolo (2021).*

Source: Adapted from Nussbaumer et al. (2012) and Le Roux & Chourmet-Nkolo (2021). Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017)

The reason for the choice of this indicator is three-fold. Firstly, the indicator illustrates the multi-faceted nature of deprivation with regards to energy services, and although it does not capture affordability explicitly, the use of certain energy sources and electrical appliances is indirectly suggesting affordability issues and the ability to use an energy service respectively (Nussbaumer et al., 2012; Le Roux & Chourmet-Nkolo, 2021). It has the advantage of uncovering both multidimensionality and intensity compared to unidimensional measures, such as the TPT (Abbas et al., 2021). Furthermore, the MEPI has been used in numerous reputable papers, indicating its degree of robustness, and it allows for a point of comparison between this analysis and pre-existing literature. Lastly, the data employed in the construction of the MEPI is available in household surveys and typically of a good quality, with regards to missing data points and outliers, relative to expenditure and income-related variables (Le Roux & Chourmet-Nkolo, 2021).

above. Energy usage outside the household for the purposes of production is not within the scope of the analysis (Mendoza et al., 2019). The deprivation score of household-i ($DS_{i)}$ subsequently becomes:

$$DS_i = w_1 X_1 + \cdots + w_d X_d \tag{3.3}$$

whereby $\sum_{d=1}^{d=6} w_d = 1$ (Alkire and Santos, 2011; Nussbaumer et al., 2012). The dimensions are weighted according to the weights adopted by Le Roux & Chourmet-Nkolo (2021; pg. 9); however, many papers raise the issue of the arbitrary assignment of weights as the significance of certain energy dimensions may differ according to the context (Nussbaumer et al., 2012; Israel-Akinbo et al., 2018). To check the sensitivity of the dimension weights used, I constructed two alternative measures whereby different weighting is applied according to the approaches of Israel-Akinbo et al. (2018) and Mendoza et al. (2019) respectively[20]. These alternative MEPIs will be employed in the empirical section for the purposes of a robustness check.

Secondly, the index requires setting an energy poverty cut-off (k) that is indicative of the weighted sum of deprivations household-i must be deprived of to be considered multidimensionally 'energy poor'. Nussbaumer et al. (2012) reasons that $0.3\dot{3}$ represents the level in which a household is at least deprived in the cooking dimension – which is deemed to

[20] Refer to Appendix A for the alternative dimension weights and their MEPI Headcount Ratio, Intensity and Adjusted Headcount.

be the central energy service of a household (Pachauri et al., 2004). Therefore, I define the energy poverty cut-off at a point where $DS_i \geq k$, where $k = 0.3\dot{3}$. I was able to construct a binary MEPI variable whereby households with a deprivation score greater than $0.3\dot{3}$ are considered energy poor (=1), and equal to zero otherwise. The MEPI has the added advantage of MEPI estimation at the national level, which can be decomposed by subgroups (Nussbaumer et al., 2012).

Table 5 MEPI Headcount Ratio, Intensity and Adjusted Headcount by wave

Wave	Headcount ratio (H)	Average Intensity (A)	Adjusted Headcount Ratio (M0)
1	0.357	0.700	0.250
2	0.288	0.701	0.202
3	0.201	0.697	0.140
4	0.168	0.857	0.114
5	0.125	0.640	0.080

Note: Stata's mpi was used to calculate the estimates shown in the above table and the decomposition by wave (Pacifco & Poege, 2017). Estimates are weighted using wave 5 panel weights made available in the NIDS dataset. Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

Table 5 above highlights the change in the headcount ratio, average intensity and adjusted headcount ratio across the waves. The calculations for these metrics are included in the Appendix.[21] All estimates pertaining to the before-mentioned variables decrease over the 10-year period. The headcount ratio declined from 0.357 in wave 1 to 0.125 in wave 5 and the proportion of households that were in multidimensional energy poverty, with a deprivation score of at least 0.33, was suggested to decline from 35.70% to 12.50%. With regards to the Average Intensity (A), we can see that households were deprived in 70% and 64% of the weighted indicators in wave 1 and wave 5 respectively, indicating a decline over time. In comparison to Table 3, the percentage of households in multidimensional energy poverty is generally greater than the proportion using the TPT. This highlights that households in South Africa experience both issues of energy access and affordability.

[21] Refer to Appendix B for how the national MEPI is calculated and for estimations at the national level by wave.

Table 6. Deprivation rate of energy dimensions and contribution of energy dimensions to MEPI, wave 1 vs. wave 5

	Households deprived of indicator (%)		Contribution of indicator[22] (%)	
Dimension	**Wave 1**	**Wave 5**	**Wave 1**	**Wave 5**
Lighting deprived:				
No access to electricity grid	17.89	5.66	14.3	13.3
Cooking deprived:				
No electric/gas stove	31.28	10.43	22.7	20.4
Does not cook with electricity, LPG/ solar	32.29	15.8	22.5	25.1
Education and entertainment deprived:				
Does not own TV/ radio/ computer	90.7	87.33	18.7	20.4
Telecommunication deprived:				
Does not own mobile	17.9	8.16	6.5	6.2
Asset ownership:				
Does not own freezer/ fridge	39.26	18.37	15.4	14.5

Note: Unit of analysis is at the household level. Panel weights are applied, and clustering and stratification of the standard errors are taken into account. Waves 2, 3 and 4 are omitted to highlight the overall change in the ten-year time period (between 2008 and 2017).

Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

The next few paragraphs serve to conduct a preliminary analysis of the MEPI variable using the NIDS dataset. Table 6 and the proportion of households that were in multidimensional energy poverty, with a deprivation score of at least 0.33, was suggested to decline from 35.70% to 12.50%. With regards to the Average Intensity (A), we can see that households were deprived in 70% and 64% of the weighted indicators in wave 1 and wave 5 respectively, indicating a decline over time. In comparison to Table 3, the percentage of households in multidimensional energy poverty is generally greater than the proportion using the TPT. This highlights that households in South Africa experience both issues of energy access and affordability.

[22] The contribution of dimension j for MEPI and poverty cut-off k is: $\emptyset_j^0(k) = w_j \frac{h_j(k)}{M_0}$, for each j = 1, …., d (Alkire et al., 2015; pg. 27).

Table 6 above describes the rates of household deprivation in each indicator that make up the MEPI and its contribution to the MEPI. Overall, the findings point to decreased energy deprivation in all indicators between wave 1 and wave 5. Specially, access to the electricity grid used for lighting purposes increased by approximately 12 percentage points between wave 1 and wave 5. Government programs to increase grid access, especially amongst rural areas, is most likely a reasonable explanation for this trend (DoE, 2013). The most noteworthy difference in deprivation rates between waves belongs to the cooking indicator and asset ownership. With regards to the cooking dimension, 32,29% of the population did not cook with electricity, LPG or solar. This could suggest energy-stacking behaviour of South African households due to the relatively high monetary value of modern energy sources compared to traditional alternatives (Madubansi & Shackleton, 2006; Makonese et al., 2020). However, 15,80% of households cooked with modern energy fuels in Wave 5. Across both waves, households are most deprived in the education/ entertainment indicator and there is not a large change in access rate between the years – which might explain the large contribution it makes to the MEPI.

Table 7 Energy access rates by settlement type and wave

	Area: Urban		**Area: Rural**		**Total**	
	Wave 1 (%)	**Wave 5 (%)**	**Wave 1 (%)**	**Wave 5 (%)**	**Wave 1 (%)**	**Wave 5 (%)**
Main cooking fuel						
Electricity	83.34	91.90	48.70	70.82	65.52	83.23
Gas	4.14	3.22	1.44	1.95	2.99	2.70
Paraffin	8.65	3.02	11.51	25.00	9.95	2.80
Wood/ coal	3.87	1.59	40.11	24.10	18.47	10.86
Main lighting fuel						
Mains electricity	91.87	95.68	69.80	90.85	81.87	93.83
Paraffin	1.77	0.87	3.44	1.19	2.53	1.00
Candles	5.94	2.62	26.10	6.51	15.11	4.22
Solar energy	0.00	0.25	0.53	1.41	00.24	00.73
Household has electricity	90.68	91.26	69.14	85.54	80.88	88.91
Access to elec. appliance						
Elec./gas stove	80.45	93.69	53.91	84.90	68.36	90.07
Fridge/ freezer	72.62	88.25	50.47	78.33	62.54	84.23
Radio/ TV/ computer	12.40	17.45	2.30	6.77	7.80	13.05
Mobile phone	84.28	91.49	78.29	92.44	82.10	91.84

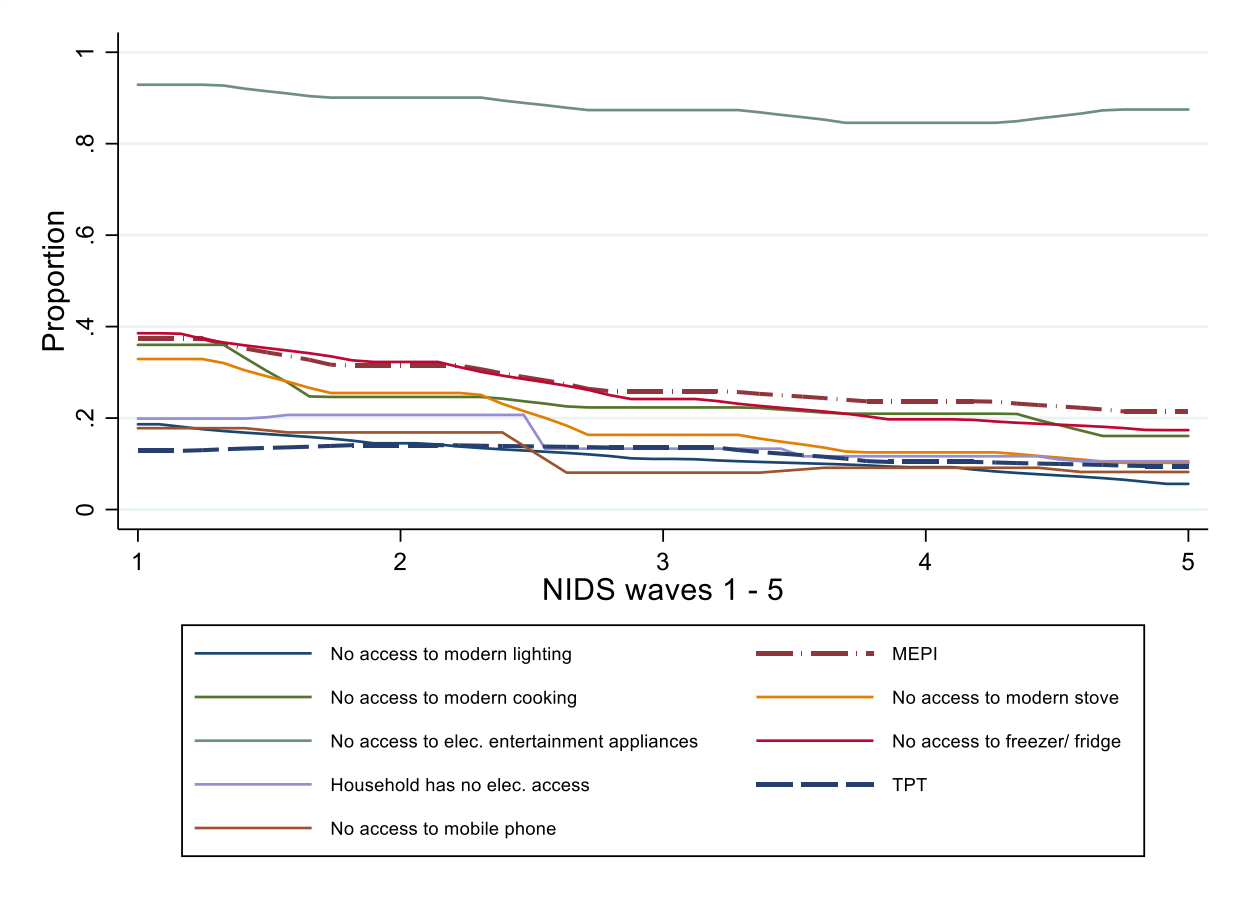
Note: Analysis is at the household level. Estimates are weighted and standard errors are corrected for clustering and stratification. Regarding the cooking and lighting fuel types, the columns do not sum to 100 due to the additional categories that had less than a 1% adoption. Waves 1, 2 and 3 are omitted to highlight the overall change in the ten-year period (2008 to 2017).
Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

In light of the above paragraph, Table 7

Table 7 shows the access rates to various energy sources for households by living area (rural or urban) and compares these rates in wave 1 to those in wave 5. There are remarkable disparities between urban and rural areas: generally, households residing in rural areas are shown to rely more on traditional biomass fuels for cooking and lighting. This is seen in the high proportion of rural households using wood/coal (40.11% for wave 1 and 25.10% for wave 5) for cooking and candles (26.10% for wave 1 and 6.51% for wave 5) versus the negligible proportions for these energy sources in urban areas. Grid and other energy-related infrastructure in rural areas during South Africa's Apartheid regime was severely lacking (Gaunt, 2003). The low energy access rates in rural areas, in earlier waves especially, may be because of delays in the democratic government's infrastructure roll-out (Bhorat & van der Westhuizen, 2013). In rural areas, a large percentage of households still rely on traditional energy sources and lack ownership to electrical appliances, despite increased electricity access rates, which confirms the believed energy-stacking behaviour within these households (Madubansi & Shackleton, 2006). Furthermore, the prevalence of high poverty rates in rural areas could also account for these estimates as income is regarded as a critical factor in modern cooking fuel adoption in South Africa (Tait, 2015).

A further analysis of the MEPI and its constituents is presented in Figure 3, which serves to augment the previous discussions. In addition, the TPT indicator is included as a point of comparison. Consistently, a decline in overall MEPI and its dimensions are observed across the ten-year period over which NIDS spans. The downward trend is most striking in the MEPI Headcount itself as it is shown to decline by close to 20 percentage points. The proportion of households spending more than 10% of their income on energy sources (TPT) is significantly lower than the MEPI Headcount across all waves. Furthermore, the decline of the TPT is relatively more gradual. The proportion of households deprived of electrical entertainment appliances (television, radio or computer) remains persistently high across all five waves. Only 22% of South African households owned computers (StatsSA, 2019), which might explain the high proportion of households deprived of entertainment appliances. South Africa's high data costs, digital literacy and low internet access rates are reasons offered for why computer ownership is low (Hawthorne & Grzybowski, 2019).

Figure 3 Evolution of MEPI and its constituent dimensions



Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

3.3. Individual development outcomes in the NIDS panel

In this sub-section, I focus on the preliminary associations that exist between the three general development outcome streams of focus – namely, health, labour market outcomes and human capital development.

3.3.1. Health outcomes

The World Health Organisation (WHO) defines *health* as the "*state of complete physical, mental and social well-being and not merely the absence of disease or infirmity*" (WHO, 2006; pg. 1). Based on this definition, I consider four different variables relating to adult health, namely an *objective health* measure (index), *life satisfaction* (binary), *depressed* (binary) and *overweight* (binary). A child's health status is considered using an anthropometrical measure, namely stunting.

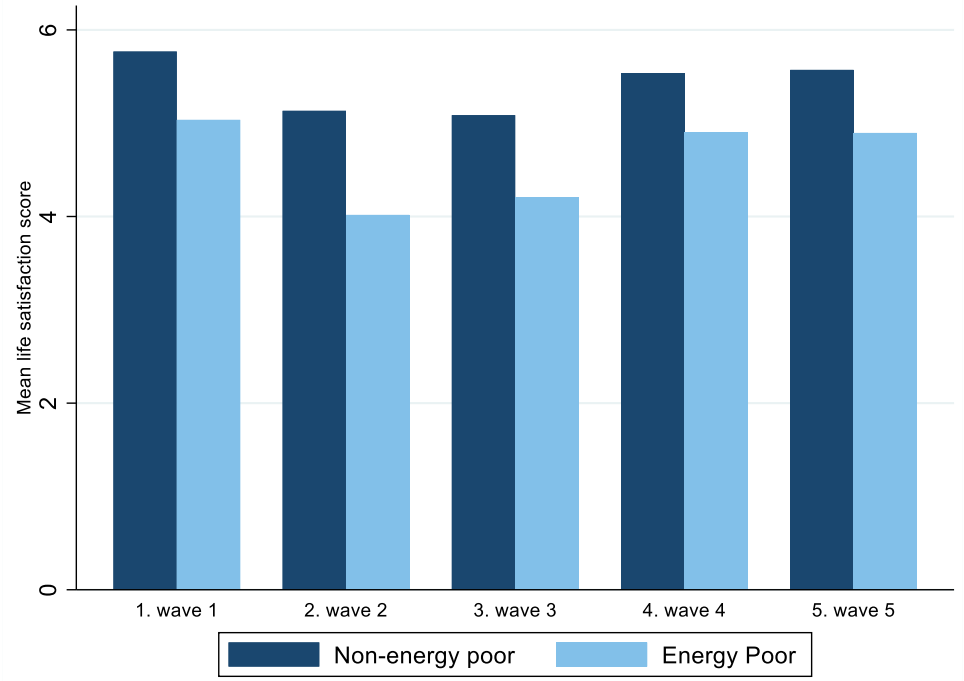
A proxy for an individual's objective health status was created and subsequently used in my regression specification(s). The variable was made by summing the total number of bad health conditions[23] that an adult individual had suffered over the last 30 days. Another variable (*overweight)* created to capture an adult's objective health was a binary variable reflecting whether an individual is considered overweight (a body mass index (BMI) greater than 25) or not. The *overweight* variable is also employed as a dependent variable in the regression(s) below. The preliminary associations between these two variables and the presence of energy poverty are shown in the Appendix C.

I also capture the psychological effect that energy poverty has on health by using *life satisfaction* variable as it is regarded as adequate insight into an individual's welfare (Delugas & Brau, 2021; Stoop et al., 2019). The variable is binary in nature, reflecting whether an individual is satisfied with life or not, and has been used in a number of studies (Welsch & Biermann, 2014). Despite the risk of self-reporting bias, Chin (2010) notes the importance of life satisfaction variables as it often dictates the individual's ability to engage in caretaking roles and employment responsibilities. Furthermore, prior literature notes the importance of individual satisfaction in welfare analyses as it is a valuable proxy of individual utility (Delugas & Braum, 2018). The original NIDS satisfaction variable (*a_wbsat)* is ranked from 1 ('very dissatisfied') to 10 ('very satisfied'). I used a binary version of the variable, reflecting whether an individual is satisfied (score >= 5) or not, in my regression specification(s). Figure 4(a) below illuminates an obvious trend across all 5 waves: individuals living in energy poverty generally have a lower life satisfaction score. This trend confirms the narrative established by the literature Delugas & Brau, 2021; (Lin & Okyere, 2020; Zhang et al., 2021; Nie et al., 2021). Figure 4(b) reports the distribution of life satisfaction across the two MEP cohorts for all waves. In the left-hand panel, relative to the right-hand panel, the distribution of non-energy impoverished households is skewed to the right, suggesting that individuals living in energy poverty generally experience lower levels of life satisfaction. This is expected given the strong relationships that are thought to exist between access to energy and social welfare.

[23] The NIDS Adult Questionnaire includes yes/no questions for fever, persistent cough, cough with blood, body ache, headache, back ache, joint pain, diarrhoea, painful urination, swelling of ankles and severe weight loss (SALRDU 2008; 2010; 2012; 2015; 2017).

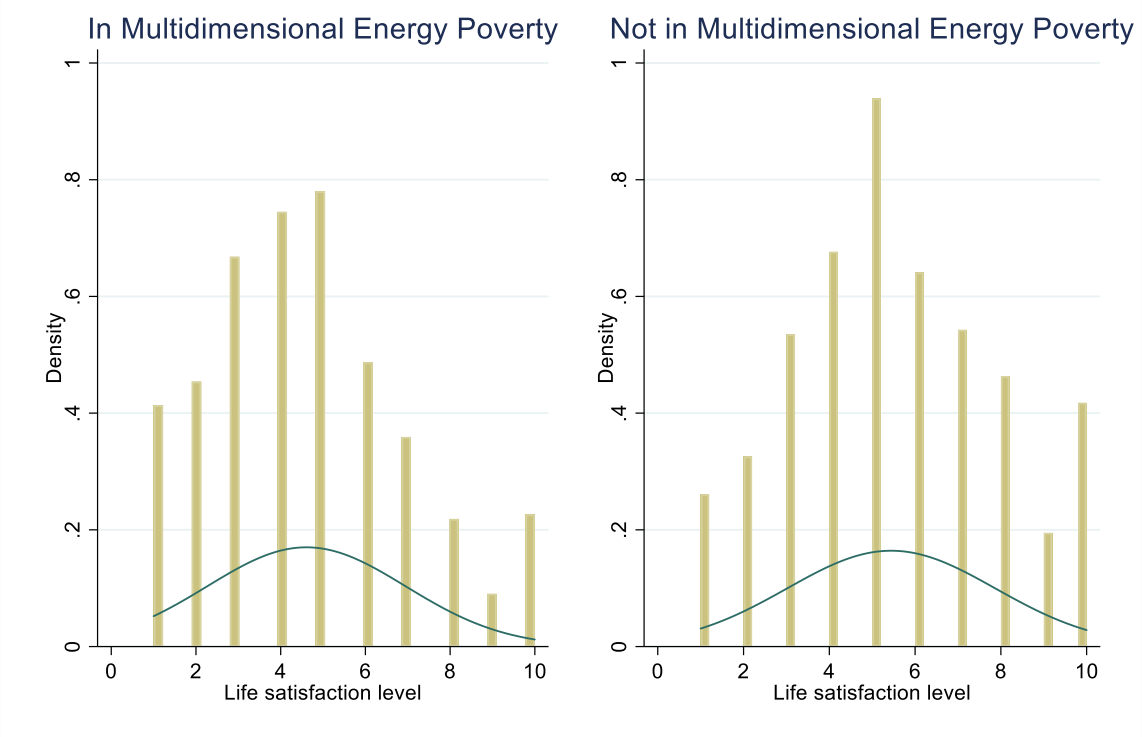
Figure 4 Life satisfaction level by MEPI status

a.) Mean life satisfaction score by energy poverty status (MEPI) and wave



Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017). Sample weights applied.

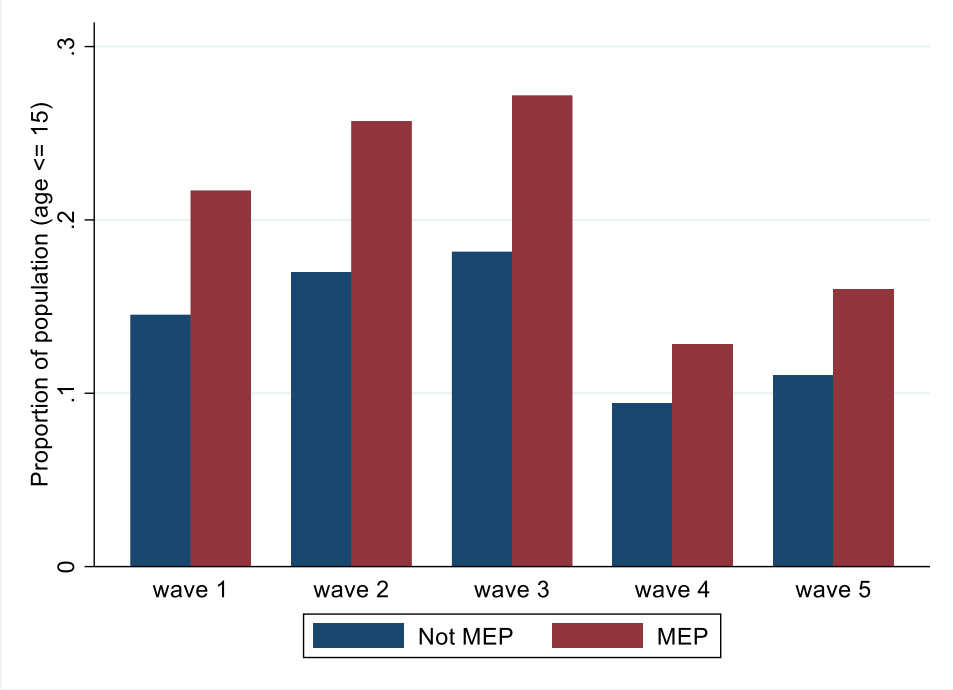
b.) Density distribution of overall life satisfaction by energy poverty status (MEPI)



Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

Furthermore, studies point to the fact that health impacts of energy poverty are typically more severe among children than adults (Thomson et al., 2003). For this reason and as it is commonplace, I consider a child's anthropometric measures, creating binary indicators to depict whether a child is considered stunted. The derived NIDS dataset provides the anthropometric variable needed to create the stunted dummy. It must be cautioned that there is a substantial rate of missing data with regards to the 'stunting' variable – roughly 15% the data points are missing24. Figure 5, panel (a) and (b), indicates that chronic malnutrition for children is strongly affected by multidimensional energy poverty, which ties in with the evidence found in Fay et al. (2005)'s study.

Figure 5 Proportion of children stunted by multidimensional EP status and wave



Notes: Sample weights applied.

Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

3.3.2. Labour market outcomes

The discussion of energy poverty and energy-access literature also highlighted the various impacts that household energy deprivation has on various labour market outcomes. The NIDS dataset provides a host of variables relating to an individual's labour market outcomes. I use the following key labour market indicators as defined in Table 1 above: strictly unemployed;

[24] Missing data points are due to a respondent's refusal or inability to answer and are not imputed in this paper.

broadly unemployed; labour force participation and weekly hours worked. Both the unemployment and labour force participation variables were created and are used in the regression specification(s). As noted by prior research, a gender lens can be applied to this sub-section to ascertain the impacts of energy poverty by gender (Grogan, 2016).

Table 8 Key labour market indicators by gender and energy poverty status

	Multidimensional Energy Poor		Multidimensional Non-energy Poor	
	Male	**Female**	**Male**	**Female**
Strict unemployment rate (%)	20.71 (0.015)	32.07 (0.015)	15.00 (0.009)	24.47 (0.009)
Broad unemployment rate (%)	24.69 (0.018)	38.74 (0.014)	17.76 (0.010)	27.94 (0.010)
Strict labour force participation rate (%)	57.37 (0.020)	46.19 (0.020)	63.46 (0.010)	55.92 (0.009)
Mean weekly hours worked	15.62 (1.183)	8.82 (0.529)	19.80 (0.615)	14.27 (0.415)

Note: Estimates are weighted, and standard errors are corrected for clustering and stratification. Standard errors are reported in brackets. Estimates are for individuals who are considered to be in the working population age group (ages 16 to 64).

Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

Key labour market indicators by energy poverty status and gender are compared in Table 8 above. The trend suggested by the estimates are illuminating. Firstly, individuals residing in multidimensional energy poor households exhibit worse labour market outcomes. When disaggregating by gender, energy poverty has a more pronounced effect on the labour market outcomes of females compared to their male counterparts. For instance, females not in energy poverty work roughly six hours more, on average, than those in energy poverty; meanwhile, their male counterparts work roughly four hours more per work. These findings confirm the points noted by Rathi & Vermaak (2018) and Dinkelman (2011) whereby rural electrification was shown to contribute to the success of labour market outcomes for females in South Africa.

3.3.3. Human capital development

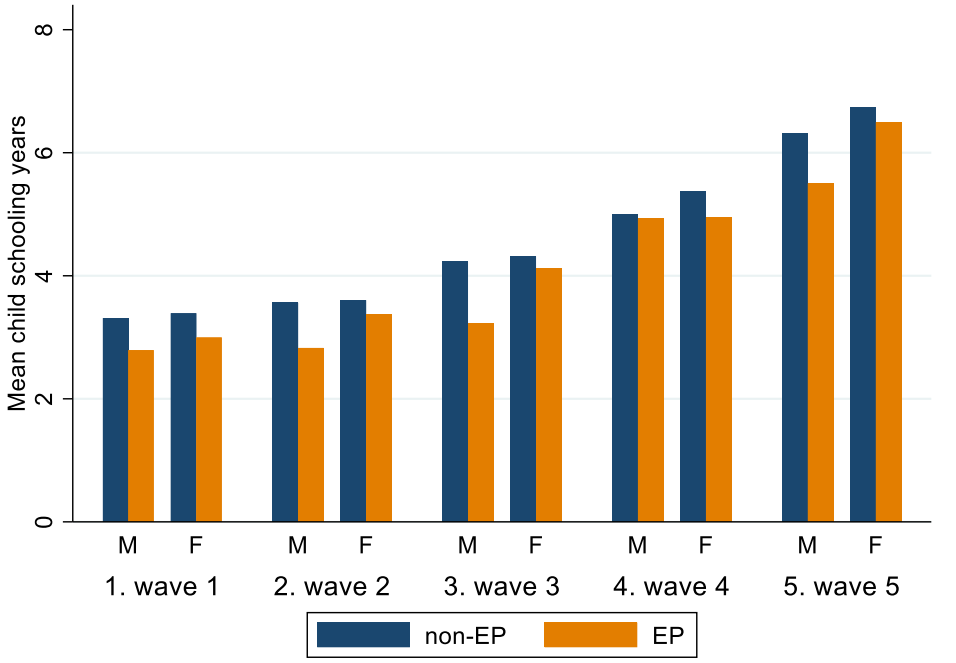
The third outcome stream that is considered concerns the human capital development of children. I look at two indicators and include them in my regression specifications: the number of schooling years attained and a binary variable indicating whether a child missed school in the last 30 days or not. The latter variable is made by recoding the variable available in the

NIDS dataset that captures the number of school days missed. This variable will elucidate a child's involvement in household chores and thus the willingness for parents to advocate a child's education (Ahmad et al., 2014). The number of schooling years variable is chosen to reflect the likelihood of pupils advancing in their education when constraints associated with energy poverty are removed. I use NIDS' derived education variable to create a variable pertaining to the number of education years an individual has attained. I find a non-response rate of 1.19% amongst children aged 0 to 15. As noted in the literature section, energy poverty can affect child's education in both the short-run (through school attendance) and long-run (through accumulation of education), hence the choice of both these variables (Ansari & Pianta, 2019; Liu et al., 2021).

Numerous authors suggest that some form of household energy deprivation has adverse effects on a child's educational attainments (IEA, 2009; Karimu et al., 2018). This is confirmed by Figure 6(a.) and (b.) below which depicts a highly suggestive positive association between human capital development and energy poverty. Consistently, children in households that are not multidimensionally energy poor attain higher years of schooling, on average. Children residing in multi-dimensional energy poor households are also shown to miss more days of school in a month, on average. However, in some waves and when considering energy poor households, female children are indicated to attain more years of schooling or miss more school days than males. This is contrary to the suggestions made by prior literature on the subject (Lockwood & Pueyo, 2013).

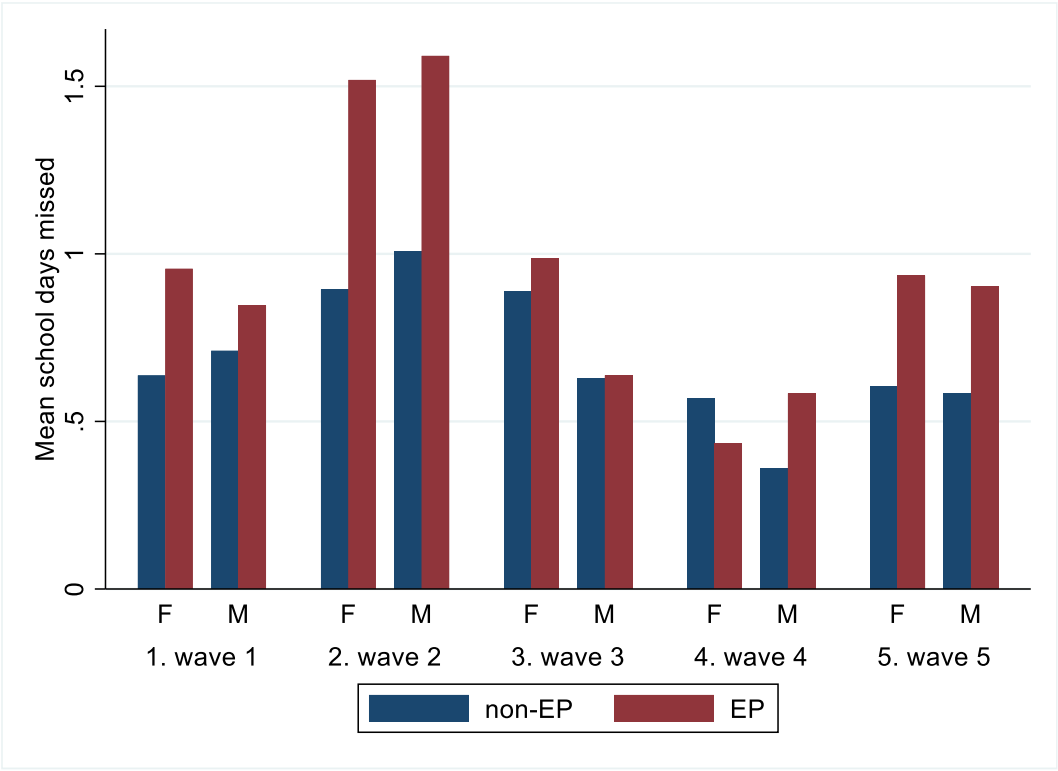
Figure 6 Education-related outcomes and MEP status

a.) Years of education attained by gender and wave



Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

b.) Mean number of school days missed by gender and wave



Notes: Sample weights applied.
Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

3.4. Overall Summary Statistics

This sub-section indicates the summary statistics (mean and standard error) on all the variables employed, disaggregated by energy poverty status and shown for wave 1 and wave 5, in the econometric specification. Due to the fact that the previous subsections included detailed information on the various outcomes variables (health, labour market and education), this discussion will serve the purpose of providing insight into the individual and household-level covariates by multidimensional energy poverty status.

With regard to individual-level co-variates, energy poor households are shown to be younger by two years, on average, than non-energy poor households. The gender-ratio is roughly even between the two comparison groups. Education levels for a child's mother are higher across both waves for non-energy poor households on average; one can also say the same for an adult individual's years of education. Both of these variables are indicated to be significant. The racial categories firstly illustrate that the data predominately refers to the African race when considering the African race (64,418) observation numbers in comparison to other race groups. Secondly, the race variables illuminate the continued reality of South Africa's post-apartheid context, whereby black South Africans still lack access to basic services and infrastructure (Bhorat & van der Westhuizen, 2013), as depicted by the suggestion that, in wave 1, 98% of African individuals reside in households existing in multidimensional energy poverty compared to the 80% that are not energy poor. This is seen against the stark contrast of virtually negligible proportions of the other racial groups living in energy poverty.

The household-level co-variates also show the narrative that households in energy poverty are generally less well-off and disadvantaged from multiple perspectives. Households in energy poverty are more likely to be in rural areas, which is synonymous with the fact that these areas were neglected with regards to infrastructure roll-out during the Apartheid regime (Gaunt, 2003). Furthermore, energy poor households lack access to other key infrastructures – such as adequate sanitation and water – compared to non-energy poor households. Tying in with this story, we see that energy deprived households have lower household incomes: in both waves, energy-poor households had an income of at least R5000 less than non-energy poor households. This variable is significant at the 1% level and suggests that there is a certain degree of overlap

between household wealth and energy poverty. Likewise, members residing in energy poor households are shown to allocate smaller amounts to monthly food expenditure.

Table 9 Definition of key variables and summary statistics by multidimensional energy poverty status of household

	Means (standard error)				
	Wave 1		Wave 5		
Variable	**Energy poor (1)**	**Not energy poor (2)**	**Energy poor (4)**	**Not energy poor (5)**	**N**
Health Outcomes (Adult, Age > 15)					
Life satisfaction	5.01 (0.13)***	5.73 (0.09)***	4.91 (0.13)***	5.58 (0.07)***	47,917
Overweight	0.42 (0.15)***	0.53 (0.01)***	0.38 (0.02)***	0.51 (0.01)***	46,975
Objective health measure	0.44 (0.02)	0.41 (0.01)	0.52 (0.02)*	0.49 (0.01)*	75,786
Health Outcomes (Child, age <= 15)					
Child is stunted	0.21 (0.02)***	0.15 (0.01)***	0.15 (0.03)*	0.11 (0.01)*	22,210
Labour Market Outcomes (Working Age Population, Ages 15 – 64)					
Employed	0.63 (0.02)*	0.68 (0.02)*	(0.70) (0.03)***	0.78 (0.01)***	25,825
Unemployed (strict)	0.23 (0.02)*	0.19 (0.01)*	0.29 (0.03)***	0.22 (0.01)***	48,501
Unemployed (broad)	0.29 (0.02)**	0.23 (0.01)**	0.25 (0.02)**	0.20 (0.01)**	50,198
Labour force participant (strict)	0.47 (0.02)	0.50 (0.01)	0.57 (0.02)***	0.61 (0.01)***	75,786
Labour force participant (broad)	0.52 (0.02)	0.54 (0.54)	0.54 (0.02)	0.60 (0.01)	75,786
Number of hours worked weekly	11.32 (0.82)**	14.37 (0.76)**	15.02 (1.05)*	17.17 (0.49)*	74,628
Child Education-related Outcomes (Age <= 15)					
Education years	2.98 (0.11)***	3.36 (0.10)***	5.98 (0.17)**	6.54 (0.08)**	29,247
Number of school days missed	0.90 (0.07)***	0.67 (0.07)***	0.92 (0.16)****	0.59 (0.08)****	15,328
Individual Covariates					
Age	23.02 (0.31)***	25 (0.39)***	32.34 (0.45)	33.15 (0.30)	75,786
Age-squared	847.82 (19.22)***	948.88 (28.24)***	1372.46 (37.34)	1416.85 (25.43)	75,786
Gender: Female	0.53 (0.01)	0.53 (0.01)	0.52 (0.02)	0.53 (0.01)	75,786
Mother's education (for ages <= 15)	7.58 (0.23)*	10.00 (0.17)*	7.73 (0.28)***	10.21 (0.16)***	14,663
Marital status (for ages > 15)	0.36 (0.02)**	0.40 (0.02)**	0.27 (0.02)**	0.33 (0.01)**	52,016
Smoke (for ages > 15)	0.18	0.17	0.19	0.17	46,895

	(0.01)	(0.01)	(0.02)	(0.01)	
Race: African	0.98 (0.01)***	0.80 (0.03)***	0.94 (0.02)***	0.85 (0.02)***	64,418
Race: White	0.00 (0.00)***	0.07 (0.01)***	0.00 (0.00)***	0.05 (0.01)***	3,554
Race: Coloured	0.03 (0.01)**	0.10 (0.03)**	0.06 (0.02)	0.08 (0.02)	5.941
Race: Indas (Indian/Asian)	0.00 (0.00)*	0.03 (0.02)*	0.001 (0.00)	0.02 (0.02)	1,538
Education years (for ages > 15)	7.61 (0.15)***	9.74 (0.10)***	8.14 (0.15)***	10.02 (0.07)***	51,980
Household Covariates					
Household size	3.38 (0.11)	3.48 (0.11)	2.01 (0.07) *	2.14 (0.04)*	24,609
Area type: Urban	0.42 .(004)	0.71 (0.03) ***	0.45 (0.03)***	0.65 (0.02) ***	24,570
Access to water	0.82 (0.03)***	0.97 (0.01)***	0.83 (0.02)***	0.96 (0.01) ***	24,565
Household owner	0.79 (0.03)	0.74 (0.02)	0.65 (0.03)	0.64 (0.01)	24,578
Household monthly income (ZAR)	1885.914 (87.21)***	6265.76 (553.31)***	5416.26 (1341.29)***	10274.71 (481.45) ***	24,609

*Note: Province variable omitted. Wave 5 panel weights are applied, and the survey design elements of clustering and stratification are considered to reflect the appropriate standard errors. Standard errors are reported in brackets. *** p<0.01, ** p<0.05, *p<0.1.*

Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

Chapter 4. Modelling Energy Poverty Effects

The energy poverty, with regards to both the MEPI and the TPT, situation in South Africa is clear. Energy poverty, especially in its multidimensional form, is still prevalent amongst a large majority of the population, and is even more pronounced amongst the lower income groups, rural areas and African sub-population. This paper is set out to provide evidence of some level of association, and a causal effect, between human development indicators and energy poverty. In this chapter I unpack the extent to which energy poverty in the country has a causal effect on reported development indicators using all five waves from the NIDS dataset. As discussed, literature points to a strong nexus between energy poverty and lower development outcomes (Khandker et al., 2012) – this was further cemented by a preliminary overview of the data. Econometric techniques used to estimate the causal effects of energy poverty, in its various types of measurement indicators, have gone through different forms. Both cross-sectional and longitudinal methods have been previously utilised to isolate the effects of energy poverty on development indicators. Recent papers have gone further by using instrumental variable (IV) approaches to correct for potential endogeneity problems associated with Ordinary Least Squares (OLS) and Fixed Effect (FE) specifications.

4.1. Review of Energy Poverty Modelling Methods

Prior literature has focused on adopting regression techniques as the primary tool for estimating the effect of energy poverty at a household and individual level. Typically, such studies use human wellbeing/ development indicators – educational, health and economic – as dependent (outcome) variable(s) of interest and an energy poverty variable as the main regressor. In instances where panel data is available, and thus welfare indicators of individuals are compared over time, the fixed effects (FE) approach enables authors to control for time-invariant unobserved heterogeneity correlated with household energy poverty and welfare indicators (Rathi & Vermaak, 2019; Zhang et al., 2019; Lin & Okyere, 2021; Nie et al., 2021; Mohan, 2021; Cheng et al., 2021). For instance, living in a state of energy poverty may induce a sense of embarrassment or low self-esteem in individuals as they are unable to live comfortably in comparison to their peers (Lin & Okyere, 2021). Therefore, children may perform worse at school and subsequently drop out as a result of such a situation. For older individuals, low self-esteem may deter them from participating in the labour market while their counterparts (those

who are not energy poor) are more motivated and able to make use of labour market opportunities.

However, recent literature has acknowledged the presence of potential endogeneity in energy poverty OLS and FE models, which may result in biased estimates, due to missing variables, simultaneity bias or reverse causality. With regards to the latter, an individual's welfare status may affect income levels and therefore affect their energy poverty status. Prior literature suggests a significant relationship between income poverty and development indicators, and a nexus between income poverty and energy poverty (Chaudry & Wimer, 2016; Dahl & Lochner, 2012). Intuitively, it reasons that a model including energy poverty takes into account income poverty to a degree, resulting in the overestimation of energy poverty effects. Secondly, the model may suffer from reverse causality if households with better labour market outcomes/ health status (which also affects labour market outcomes) are more able to demand modern energy sources. Furthermore, energy poverty may not be randomized and thus endogenous to development indicators: rural grid infrastructure could be more cost-effective in areas that already have unmeasured economic advantages, giving effect to better welfare outcomes, and thus a household's energy poverty status may suffer from omitted variable bias. Lastly, unmeasured political economy motivations, regardless of customer demand or the cost-effectiveness of an energy provision, may account for the locational provision of energy-related infrastructure (Dinkelman, 2011; Rathi & Vermaak, 2018). This discussion provides several reasons that motivate moving away from the standard econometric model(s) you can apply to energy poverty-welfare studies, such as OLS and panel FE approaches.

To address the problem of endogeneity present in energy poverty OLS and/or panel FE models, it is not uncommon for authors to utilise an instrumental variable approach (IV) – often undertaken with two-stage least squares (2SLS) regression techniques. There is a general consensus amongst economic literature that finding suitable instrumental variables is challenging (Baum & Schaffer, 2003); therefore, this warrants a discussion on the previous IVs adopted. Authors have chosen 'access to piped water' as an IV for accessibility to energy services as it is reasoned that it proxies local infrastructure, which is unlikely to directly affect an individual's development outcome (Zhang et al., 2019). Zhang et al. (2019) and Cheng et al. (2021) also employ the 'average provincial share of people in EP' as a proxy for affordability to energy services. Similarly, Sedai et al. (2021) employs the 'average hours of household electricity at the district level other than household-*i*' as an instrument for a household-*i*'s hours of electrification. Accordingly, one could expect that the higher the

likelihood of other households in the district using biomass as an energy source, the more probable it is that household-*i* does not use clean, modern energy sources. The share of the district population using biomass as a fuel source should also not have a direct influence over a household's income, assets and expenditure (Sedai et al., 2021). However, the literature cautions that, since it is estimated at the provincial level, this IV may cause greater variations in the estimated model and thus lead to statistical insignificance. Furthermore, energy poverty at the local level might have general equilibrium effects on welfare outcomes (Rathi & Vermaak, 2018). Despite this, any biases that arise because of household-level reverse causality is subsequently eliminated using a district-level variable (Dang & La, 2019).

The most promising instrument in the energy poverty-welfare model, which is also widely adopted by researchers, is 'electricity and/or liquified petroleum gas (LPG) prices' (Churchill et al., 2020; Lin & Okyere, 2020; Nie et al., 2021; Prakash & Muntanyi, 2021; Hailemariam et al., 2021; Cheng et al., 2021). Accordingly, premised on demand theory, the prices of endogenous variables could be good candidates for IVs if the market is competitive (Khandker et al., 2012). Food prices, and more generally, commodity prices, have been used as instruments dealing with development outcome variables and income (Thomas & Strauss, 1996). Based on evidence that there exists a significant nexus between energy price and demand (He et al., 2010). Alem & Demeke (2020) illustrated the adverse effect of increased energy prices, notably the price of kerosene, on household energy poverty in Ethiopia. In the case of energy poverty, however, caution must be raised as South Africa has a regulated electricity market and the prices are determined by the National Energy Regulator South Africa (NERSA) and demand is more conditioned on availability (le Grange, 2019). Furthermore, the price of electricity is lower for indigent households qualifying for FBE and electricity price also includes connection fees, which varies by distance from the electricity,

In light of the widespread adoption of energy prices as IVs in energy poverty-welfare models, it is necessary to further investigate the strength of this supposed instrument. Valid instruments ought to satisfy two conditions. Firstly, there must exist a canonical correlation between the instrument (energy prices) and the endogenous variable (energy poverty). Increased energy prices, which are exogenously set by South Africa's energy regulator, can lead to reduced energy demand. In turn, energy prices can results in lower use of modern energy sources – so much so that households could fall into a state of energy poverty (Kahouli, 2020). The second condition raised is the exclusion restriction, which states that the instrument can only affect the outcome variable through the endogenous variable (Woolridge, 2012). Increments in energy

prices reduce access to modern, clean energy sources (such as gas/electric stoves and electric lighting), thus worsening an individual's welfare. For instance, households may resort to traditional biofuels, which is notorious for causing indoor pollution, and poses a threat to an individual's pulmonary health. This seems to be a reasonable assumption as individuals are predominately perturbed about the effect energy prices have on the share of energy expenditure in the household budget (Prakash & Munyanyi, 2021). Therefore, the only channel through which energy prices will affect human development indicators is through energy poverty.

However, this IV also presents the concern that changes in energy prices might redirect household expenditure towards food, labour market search and education spending under household budget constraints (Kahouli, 2016). Greater expenditure on household energy appliances instead of healthcare, for instance, will redirect the household budget away from health outcomes if households prefer spending on energy over other expenses. This will therefore violate the exclusion restriction. However, household spending on energy sources is unlikely to represent a large enough proportion of the household budget to cause a significant income effect that will alter spending on health and education (Kahouli, 2020; Churchill & Smyth, 2021). Furthermore, when regarding labour market outcomes, it is unlikely that a household would reduce their labour market costs to forgo potential incomes due to changes in energy prices (Cheng et al., 2021). Lastly, following the logic of previous authors (Churchill & Smyth, 2021; Cheng et al., 2021), the mean share of energy expenditure in household income does not vary greatly between waves, as indicated in Table 10 Household energy expenditureTable 10 below, as the mean varies between 5.5% and 4.6%. Therefore, the energy expenditure as a share of household budget is not large enough to generate a great income effect to substantially impact other items in the budget. We can therefore conclude that, based on previous studies, energy prices are seemingly good IVs for the energy poverty-welfare model.

Table 10 Household energy expenditure

	Wave 1		Wave 2		Wave 3		Wave 4		Wave 5	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Household energy expenditure in last 30 days (ZAR)	128.51	6.48	176.53	10.55	244.43	13.32	250.03	14.07	293.62	15.26
Share of energy expenditure in household income (%)	5.25	0.27	5.44	0.23	5.51	0.16	4.61	0.17	4.74	0.20

Note: Wave 5 panel weights are applied, and the survey design elements of clustering and stratification are considered to reflect the appropriate standard errors.
Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

4.2. Methodology Followed

4.2.1. Pooled Ordinary Least Squares Model (POLS)

The study examines the changes in development indicators given the changes in energy poverty status over time. To begin with, I estimate a pooled ordinary least squares model (POLS), treating all five waves of NIDS are combined as cross-sections where there are repeated observations on fixed units. POLS estimates a 'classic linear regression' on the combination of cross-sections where observations are repeated on fixed units. The advantage of a POLS model is it allows for variations in the explanatory variables over time (Woolridge, 2010). For individual *i* in household *h* and survey wave *t*, the following reduced POLS equation is estimated as follows:

$$Y_{iht} = \alpha + \beta_1 EP_{iht} + \beta_2 HH_{iht} + \beta_3 I_{iht} + \varepsilon_{iht} \quad (4.1)$$

Y_{it} is the development indicator (health, education, or labour market) whilst EP_{it} represents a dummy variable indicating the energy poverty (MEPI or TPT) status of individual-i. HH_{it} and I_{it} are vectors of observable household and individual characteristics, respectively. The coefficient of focus is β_1 as it reveals whether, and the magnitude and direction, there exists a casual effect energy poverty is expected to have on an individual's development outcome. I assume ε_{it} are iid [0, σ^2].

However, in equation (4.1), the error term ε_{it} can be viewed as a composite error $a_i + u_{it}$, which consists of time-invariant individual characteristics and an i.i.d. error term respectively. In effect, a_i includes factors such as an individual's family characteristics, cultural beliefs, inherent ability, genetic predispositions *et cetera* that are not expected to change over time. Unless $corr(a_i, X_{it}) = 0$, which is unlikely to hold given the prior points, the POLS model will result in biased and inconsistent estimates.

4.2.2. Longitudinal Estimators

The study examines the change in individual development indicators given the changes in household energy poverty status. When estimating the causal effects of energy poverty status, pooled OLS regression techniques are unlikely to account for the variation induced by time-invariant confounding effects. This may result in the findings including spurious results if time-invariant unobserved individual characteristics are correlated with the explanatory variables, causing endogeneity bias (Woolridge, 2012).

I therefore follow the approach adopted by previous energy poverty literature (Rathi & Vermaak, 2019; Zhang et al., 2019; Lin & Okyere, 2021; Nie et al., 2021; Mohan, 2021; Cheng et al., 2021) and exploit the panel element of NIDS to inspect the dynamics of energy poverty and development indicators. A FE approach will allow for the elimination of individual-specific, time-invariant characteristics (a_i) that may cause biases if such unobservable characteristics in the error term are correlated with our dependent variable of energy poverty status (Woolridge, 2010). A Hausman test was performed to decide whether a Fixed-Effects or Random-Effects (RE) models is best suited for the data. Under this model, the null hypothesis assumes that the RE model is appropriate. The results of the Hausman test indicate a p-value less than 5% for all models except for that including 'stunted' as the outcome variable, and thus the null is rejected, and the FE model is preferred in all instances apart from the stunted model[25].

The FE model is estimated by subtracting the time-average model from the original model in (4.1). For individual *i* in household *h* and survey wave *t*, the following equation is estimated:

$$Y_{iht} - \bar{Y}_{ih} = \delta(EP_{iht} - \overline{EP}_{ih}) + \gamma(HH_{iht} - \overline{HH}_{ih}) + \theta(I_{iht} - \overline{I_{ıh}}) + (\varepsilon_{iht} - \overline{\varepsilon_{ıh}}) \quad (4.2)$$

Where $\bar{Y}_i = \sum_{t=i}^{T=5} y_{it}$ and $\bar{x}_{ji} = \sum_{t=i}^{T=5} x_{jit}$

The reduced equation can be represented in its time-demeaned form as:

$$\ddot{Y}_i = \delta(\ddot{EP}_i) + \gamma(\ddot{HH}_i) + \theta(\ddot{I}_ı) + (\ddot{\varepsilon}_ı) \quad (4.3)$$

The variable a_i, which forms part of the error term as the individual-specific fixed effect, is constant over time:

$$\bar{a}_i = a_i$$

, and as such, the determinants of individual development outcomes that are constant within an individual over time are eliminated. The time-variant aspect of the error term, represented by u_{it}, can be assumed to be independently distributed over *i*. Assuming that u_{it} takes on a logistic distribution, the FE-model is estimated by conditional maximum likelihood. Therefore, a

[25] The Random Effects (RE) model can similarly be used to control for unobserved individual characteristics when it is believed that the unobserved individual heterogeneity is uncorrelated with the included regressors (Woolridge, 2012). I therefore fit a RE model, using the same controls as the FE model, under the assumption that the individual effects are random and follow a normal distribution. See Appendix D for Hausman test results

contribution to the likelihood function is a result of individual's whose energy poverty status changes across the time period.

According to Woolridge (2012), FE estimation techniques require a degree of variation in the independent variations to ensure an appropriate average effect. I first consider movements in energy poverty status across the survey waves, using pooled NIDS panel data. Looking at Panel A in Table 11 below, there is a high degree of persistence with regards to those individuals not in MEP and only 7,88% of individuals MEP in wave t-1 find themselves in MEP in wave t. However, there is substantial movement out of MEP – 46,10% of individuals in MEP were able to move out of MEP in a subsequent wave. Turning to Panel B, there is once again a large degree of 'stickiness' when it comes to remaining non-poor according to the TPT approach (88,27%). However, 76,61% of TPT energy poor individuals in wave t-1 are expected to transition out of that status in the next wave. This discussion indicates how, despite a large degree of persistence in non-EP individuals, there is variation in states between the waves.

Table 11 Transition matrix of energy poverty indicator(s) between periods

Energy poverty status, *wave t-1*	Energy poverty status, *wave t*		
	Non-poor (%)	Poor (%)	Total
Panel A: MEPI			
Non-poor	92,12	7,88	100
Poor	46,10	53,90	100
Panel B: TPT			
Non-poor	88,27	11,73	100
Poor	76,61	20,39	100

Note: Each element of the matrix above indicates the probability (in percent) that an individual belongs to an energy poverty status in wave t-1, given their status in wave t. The entries sum to 100 along the columns. Sampling panel weights applied.

4.2.3. Dealing with Endogeneity

A number of authors raise the concern that the energy poverty variable is endogenous (Rafi et al). If the differences between energy-impoverished households and those not in energy poverty are systematic, this will violate the 'strict exogeneity' requirement of the FE longitudinal model, subsequently biasing the FE-estimates. For the estimates from the FE-model to be unbiased and inconsistent, the strict exogeneity assumption needs to hold – i.e.) $E(u_{it}|\mathrm{X}_i, a_i) = 0$, implying that the expected value of the error term given the explanatory variables across all five waves and the time-invariant effect is zero (Woolridge, 2012). Endogeneity arises in the

instance that unobserved characteristics affect modern energy adoption, and energy poverty in its multidimensional form, and thus the outcome of interest.

In this instance, as highlighted by previous literature, it is likely that both energy poverty indicators are endogenous in the model (Cheng et al., 2021; Lin & Okyere, 2021). Households in energy poverty may be qualitatively different to those not in a state of energy deprivation. Households in energy poverty are more likely to fall within the lower income brackets. Since income is frequently used as a proxy for socio-economic status (Kahouli, 2020), it is seen as an important determinant in both health status, labour market outcomes and educational attainment.

The assumed endogeneity of the energy poverty variable (both the MEPI and TPT) was confirmed by the 'endog' option used in STATA's '*xtivreg2*' user-written command. Unlike the Durbin-Wu-Hausman endogeneity test, this option is robust to violations of conditional homoskedasticity (Baum et al., 2007). The C-statistic, also referred to as the "GMM distance" or "Difference-in-J test", results from the endogeneity test of the endogenous regressors are presented in Appendix 0F. Under the null hypothesis, the specified endogenous regressor can be treated as exogenous (Baum et al., 2007). The output indicates that we can reject the null hypothesis that the energy poverty variable is strictly exogenous, and therefore it warrants the search for an appropriate IV.

4.2.4. Modelling the effect of energy poverty: Instrumental variable approach

The study initially looks at both POLS and FE-model(s) – however, these models are not sufficient enough to establish the causal relationship between energy poverty and outcome variables due to the issue of endogeneity bias. Unobservable factors that have bearing on energy poverty, - such as individual's expectations regarding income generation, energy efficiency of homes and room sizes – may also affect individual development outcomes (Kahouli, 2020; Prakash & Munyani, 2021). The estimation of the effect of energy poverty therefore necessitates the inclusion of an instrument that is a strong predictor of energy poverty, conditional on the covariates, but is not correlated with the outcome variable(s) of interest (Woolridge, 2012). An adequate instrument can be used as a solution for both endogeneity and measurement error issues.

Based on the prior discussion of literature, I look at electricity price as an instrument for energy poverty. Also premised on literature, as a proxy for accessibility, I include the share of the district population, apart from household-*i*, using biomass as a fuel source as an additional IV.

The major drawback in utilising the NIDS dataset, in this case, is that there is no variable for the electricity price faced by the household; therefore, I had to utilise data made available by NERSA and Eskom to construct the electricity price variable by local district municipality and wave[26]. Choice of instrument often leads to debates due to the weak associations between the treatment and IV, rendering it difficult to obtain precise estimate of causal effects (Staiger & Stock, 1997). Therefore, one needs to consider whether the instrument is sufficiently valid and strong[27].

A valid instrument needs to satisfy two conditions: (1.) relevance; and (2.) exclusion restriction. Relevance necessitates that the instrumental variable (IV) effects the probability of treatment, in this case, the energy poverty status, meaning that there is a significant correlation between the IV and energy poverty (EP) status conditional on the other covariates (X) (Woolridge, 2012). In mathematical terms:

$$Cov(IV_i;\ EP_i|X_i)\ \neq 0 \qquad (4.4)$$

The relevance condition is easily testable. The first stage regression, whereby the instrument is regressed on the outcome variable conditional on the covariates, an F-statistic greater than 10 must be yielded if the instrument were to be regarded as 'strong' (Stock & Yogo, 2005). The First-stage test indicated that there is a strong association between energy poverty and the electricity price[28] faced by a household in district *d* and wave *t*, as indicated by the sufficient magnitude and significance attached to electricity price. This effect is in line with prior literature (Davis et al., 2008; Menash & Adu, 2015). Furthermore, the strength of the instrument is supported by virtue the Cragg-Donald Wald F-statistic being greater than 10 in all models[29].

Secondly, a valid instrument also passes the exclusion restriction whereby the IV must only affect the outcome variable(s) exclusively through its effect on EP. This means that there exists no correlation between the outcome variable and the unobserved error term once the effects of EP are netted out. Authors point out that this restriction is difficult to test directly, but that knowledge on the topic at hand will assist in the model specification (Baum, 2006). As

[26] For more information on the construction of the electricity price variable, Appendix I provides a detailed discussion.
[27] For a list of other potential instruments, see Appendix G
[28] Following the papers of Lin & Okyere (2020) and Prakash & Munyanyi (2021), the district-level electricity prices are logged.
[29] Refer to Appendix J

highlighted in the extensive overview of previous energy poverty-IV literature, energy prices and the share of the population using biomass should have no causal association with an individual's health, labour force and education outcomes. One of the possible pathways through which electricity prices are expected to influence development outcomes is through energy poverty. An increase (decrease) in the price of electricity can induce households to adopt cheaper traditional (modern) energy sources to the extent in which they can be rendered energy (non) poor (Kahouli, 2020; Churchill et al., 2020; Prakash & Munyani, 2021). This logic is based on the assumption that individuals are only concerned about how the changes in energy prices affects their energy expenditures (Churchill & Smyth, 2020). However, it is important to acknowledge that there are other channels through which energy prices influences development outcomes – such as the competition it causes between household health, education or labour market expenditure and energy expenditure[30] (Kahouli, 2020). Furthermore, the substitution towards traditional energy sources is dependent on the availability of the energy sources, their efficiency and the preferences around energy sources (Ma

sera et al., 2000). With regards to the IV relating to the share of the district using biomass fuel sources, there is assumed to be a high degree of similarity in terms of infrastructure and income amongst households residing in the same district. Once household factors such as age, marital status, household income (etc.) are controlled for, there should exist a negligible relationship between energy poverty at the macro level (Zhang et al., 2019: pg. 8).

A series of additional tests were conducted to prove the appropriateness of the two chosen instruments. An under-identification test is an LM test of whether the equation is exactly identified – i.e., excluded instruments are correlated with endogenous regressors (Baum et al., 2010). The Kleibergen-Paap LM tests, reported in Appendix F, suggests significant statistics in all models, and thus I can conclude that the model is not under-identified. It is also necessary to assess whether the model is overidentified, i.e., the instrumental variables are correlated with the error term (Baum et al., 2007). I therefore employ the Hansen-J test provided by the user-written command '*xtivreg'* to assess this (Baum et al., 2007). In this instance, rejection casts doubt as to the validity of the instrument.

This paper can look to economic events that have varying effects on individuals and are not related to prior energy poverty or development outcomes. For this reason, and based on an

[30] See Chapter 4, sub-section 4.1 pg. 63 for a further discussion.

extensive amount of literature available, I utilise electricity prices as instruments for energy poverty. Therefore, I use a model that incorporates both FE and IV in order to address potential sources of endogeneity – time-invariant individual characteristics that affect EP and development outcome(s) and dynamic influences. The 2SLS-model is used to incorporate instrumental variable(s) into the model. Following previous studies, I instrument for endogenous energy poverty status using electricity prices (P_{it}) and subsequently estimate the following system of equations:

$$\widehat{M\ddot{E}\ddot{P}I_{\imath ht}} = \alpha_0 + \alpha_1 \ddot{C}_{it} + \alpha_2 P_{idt} + \alpha_3 D_{idt} + \eta_{iht} \quad (4.5)$$

and

$$y_{\imath ht}^{\cdot\cdot} = \beta_0 + \beta_1 \widehat{M\ddot{E}\ddot{P}I_{\imath ht}^{*}} + \gamma_1 \ddot{C}_{\imath t} + \varepsilon_{1\imath t}^{\cdot\cdot\cdot} \quad (4.6)$$

,where $\varepsilon_{1\imath t}^{\cdot\cdot\cdot}$ and η_{iht} are unobserved. The identification assumption is that, conditional on baseline household characteristics, household income and economic welfare of the surrounding community and individual fixed effects, the district level electricity price that a household faces does not influence the outcome variables independently of being assigned energy poverty status. Equation (4.5) is the first-stage regression whereby the effect of energy poverty is isolated. The fitted values derived from equation (4.5) are used in equation (4.6) to mitigate any endogeneity issues between energy poverty and the outcome variable(s) and produce an unbiased, consistent FE-2SLS estimate. Based on the reasons justifying the econometric specification for the energy poverty-outcome model described in the discussion above, I move on to illustrate my findings in Chapter 5.

Chapter 5. Results and Discussion

This Chapter provides the empirical results – inclusive of the baseline, panel and instrumental variable methods – and interpretations on the results. These results will be used to provide insights into the research questions at hand and to test whether energy poverty does have consequences for an individual's development outcomes, at a health, labour market, and human capital level.

5.1. Health Outcomes

I restrict the sample to the adult population (aged 15 and older) as made available in NIDS' adult questionnaire, where the outcome variables were asked to the respondents. For the full regression results, refer to Appendix K. Similar to previous energy poverty-health studies, the control variables used in these models include both individual covariates (age, age-squared, gender, non-economically active dummy, education level, married dummy, smoke dummy) and household level covariates (household income per capita, household size, whether there are dependents in the household, access to piped water dummy, dwelling type, area type, province dummy, and wave dummies) (Prakash & Munyanyi, 2021; Awaworyi Churchill & Smyth, 2021; Cheng et al., 2021; Lin & Okyere, 2019).

Table 12 below presents both the results from the POLS and FE regressions indicating the effect of the presence of household energy poverty on an individual's health. In the table, only the coefficient of interest is reported – namely, the MEP indicator, which assumes a value of 1 if the household is considered multidimensionally energy poor. Columns 1 to 8 include both the baseline OLS results and the FE results and represent the different health outcome variables under consideration. I consider four heath outcome variables viz. binary variables indicating an individual's life satisfaction, depression to capture the mental health situation, overweight and objective health index[31].

As seen in Table 12, the FE-results indicate smaller coefficients, although the direction of the coefficients are the same, compared to the POLS findings. Results show that most estimated coefficients from the FE-regression are statistically different from zero, apart from the

[31] Please refer to Table **9** for a description of the variables and their coding.

Depression dummy. With regards to Column (2), individuals living in MEP are, on average, 3.2% less likely to be satisfied with life than individuals not in MEP. This result is significant at the 1% level. Looking at Column (4), although the result is unsignificant, these individuals are more likely to be depressed than their non-MEP counterparts. These findings are in line with the hypothesis that energy poverty negatively impacts both the subjective and objective measures of an individual's mental health (Sovacool et al., 2012; Lin & Okyere, 2020; Churchill & Smyth, 2021; Nie et al., 2021). Interestingly, individuals living in MEP are shown to have a better objective health status: individuals are less likely to be overweight (-0.016**) and report a lower objective health index (-0.083**).

Table 12 Health Outcomes: Pooled OLS and Panel FE Results

	(1-OLS)	(2-FE)	(3-OLS)	(4- FE)	(5-OLS)	(6-FE)	(7-OLS)	(8-FE)
	Satisfied	Satisfied	Depressed	Depressed	Overweight	Overweight	Health index	Health index
MEPI	-0.075***	-0.032***	0.018*	0.011	-0.063***	-0.016*	-0.028	-0.083**
	(0.013)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.037)	(0.037)
Constant	0.888***	0.511	0.117***	0.962***	-0.398***	-0.762**	0.472***	6.583***
	(0.041)	(0.422)	(0.030)	(0.368)	(0.047)	(0.300)	(0.160)	(1.500)
Observati	48,013	48,013	48,013	48,013	45,975	45,975	48,013	48,013
Number of pid		12,505		12,505		12,458		12,505

*Notes: Refer to Appendix K for the full regression results. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.1; **p<0.05; ***p<0.01*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

Literature and empirical diagnostics have indicated that endogeneity is likely present in the energy poverty variable, which would render both the POLS and FE-results inconsistent (Churchill et al., 2020). To address this, turning to Table 13, I use specifications to show the effect of MEPI on adult health outcomes utilising fixed effects and panel 2SLS estimations. MEP is highly significant in models (1), (2) and (3) and associated with adverse health outcomes (-0.140** in (1); . -0.150*** in (2) and 0.088** in (3)). In Column (1), the coefficient shows that, at the 5% significance level, MEP status is expected to decrease the chance that an individual is satisfied by 14%, *ceteris paribus*, while, in Column (3), the likelihood of being overweight is expected to increase by 8.8% on average. These results confirm those from previous literature looking at the effects of energy poverty on life satisfaction (Churchill & Smyth, 2021; Nie et al., 2020) and physical health (Prakash & Munyanyi, 2021). In contrast to the findings from Lin & Okyere (2019), I found that MEP is expected to decrease the chance

an individual is considered depressed, significant at the 10% level. This might be because the magnitude of the MEP estimate differs across individuals with varying mental health statuses, as proposed by Zhang et al. (2022). The results pertaining to an individual's objective health become insignificant, although the direction of the sign changes to suggest that MEP does indeed worsen an individual's health status, in line with prior expectations (Zhang et al., 2019).

Table 13 Health Outcomes: FE-2SLS Results

	(1)	(2)	(3)	(4)
	Satisfied	**Depressed**	**Overweight**	**Health index**
MEPI	-0.140**	-0.150***	0.088**	0.112
	(0.064)	(0.055)	(0.045)	(0.222)
Observations	46,835	46,835	44,738	46,835
Number of pid	11,327	11,327	11,221	11,327

*Notes: Refer to Appendix K for the full regression results. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

In Table 14, I further disaggregate the results by gender to investigate whether MEP has differential effects given the gender of an individual. The direction of the coefficients acts in line with the results from Table 13 Health Outcomes: FE-2SLS Results, however, apart from Columns (3) and (6), the degree of significance decreases substantially. Furthermore, with reference to Figure 2 in Chapter 2.3.1, another plausible reason explaining decreased individual mental status can be attributed to the decreased access to mobile and internet connectivity or resources, resulting in a lowered sense of belonging in communities (Day et al., 2016). Females residing in energy poor households are less likely to be depressed than males; however, the female result is significant at the 5% level, suggesting that this finding has more economic bearing. As theorised by Nie et al. (2020), this could be due to socio-cultural factors: in South Africa, women living in MEP are often burdened with domestic activities that involve the use of inefficient and time-consuming energy sources (Dinkelman, 2011). On the other hand, energy poor males show a higher likelihood of being overweight, whilst this relationship works in the opposite direction for energy poor females. This confirms the results provided Prakash & Munyanyi (2021)[32]. One potential explanation relies on the assumption that MEP women are largely involved in the domestic labour of collecting biomass fuels and other such domestic

[32] Prakash & Munyanyi (2021) find that energy poverty affects the chance of obesity differently for men and women. Their results indicate that men are more likely to be obese than their female counterparts.

activities, and thus engage more regularly with strenuous exercise than their male counterparts (Reddy et al., 2000; UN, 2019). These results ultimately supports that energy poverty, as a form of poverty, is synonymous with being socially disadvantaged (Adusah-Poku et al., 2020).

Table 14 Health Outcomes by gender: FE-2SLS Results

	(1-Female)	(2-Male)	(3-Female)	(4- Male)	(5-Female)	(6-Male)	(7-Female)	(8-Male)
	Satisfied	Satisfied	Depressed	Depressed	Overweight	Overweight	Health	Health
MEPI	-0.108	-0.185	-0.126**	-0.159	-0.022	0.272***	0.104	0.140
	(0.073)	(0.118)	(0.064)	(0.100)	(0.051)	(0.082)	(0.267)	(0.384)
Observations	28,638	18,197	28,638	18,197	27,41	17,328	28,638	18,197
Number of pid	6,649	4,678	6,649	4,678	6,602	4,619	6,649	4,678

*Notes: Refer to Appendix N for the full regression results. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

As a robustness check, I will also investigation the correlation between MEP and child health. The sample is restricted to children aged 0 to 15. This is age group is targeted by NIDS' Child Questionnaire. I use the NIDS' weight-for-height z-score variable, *zwfh*, to construct a binary indicator to reflect whether a child is stunted (=1) or not[33]. The 'stunting' variable is often utilised in child health literature to indicate whether a child is considered malnourished and/or the number of cumulative infections a child has had since birth (Rafi et al., 2021; Fay et al., 2005). As seen in Table 15, the OLS specification indicates that, relative to children living in non-MEP households, MEP is expected to increase the chance that a child is stunted by 5.3%, significant at the 10% level. However, this result becomes insignificant when looking at both the FE and the FE-2SLS specifications. Interestingly, the direction of the effect changes in the FE-2SLS model, suggesting that energy poverty decreases the probability of child stunting, *ceteris paribus.*

[33] Using the available BMI variable made available in the NIDS dataset, I also created a variable to reflect whether a child was 'underweight' or not. However, this variable was not used in the regression specification due to its large number of missing values, and thus the potential bias that might arise.

Table 15 Child Health Outcomes

	(1-OLS)	(2-FE)	(3-FE-2SLS: All)	(4- FE-2SLS: Male)	(5-FE-2SLS:Female)
	Stunting	**Stunting**	**Stunting**	**Stunting**	**Stunting**
MEPI	0.053***	0.005	-0.090	-0.020	-0.025
	(0.017)	(0.015)	(0.090)	(0.132)	(0.135)
Observations	11,115	11,115	10,503	4,366	4,496
Number of pid		3,642	3,030	1,242	1,30

*Notes: Refer to Appendix M regression results. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

5.2. Labour Market Outcomes

I have restricted the sample to the working age population (aged 15 to 64) as provided by StatsSA (2002). Based on prior literature looking at labour market outcomes, I include the following control variables: individual covariates (age, age-squared, gender, education level, married dummy, smoke dummy) and household level covariates (household income per capita, household size, whether there are dependents in the household, access to piped water dummy, dwelling type, area type, province dummy, and wave dummies) (Dinkelman, 2011). Table 16 exhibits baseline OLS and panel estimates for the relationship between MEP and labour market outcomes. MEP is associated with a lower chance of being in the labour force, albeit this effect is not significant; although, it is associated with a higher probability of being unemployed (estimates are significant at the 5% level). The pooled OLS and FE results indicate that individuals residing in multi-dimensional energy poor households have a higher chance of being unemployed (according to both the strict and broad definition of unemployment) by 31 to 33%, respectively.

Table 16 Labour Market Outcomes: Pooled OLS and Panel FE

	(1-OLS)	(2-FE)	(3-OLS)	(4- FE)	(5-OLS)	(6-FE)	(7-OLS)	(8-FE)
	LF (strict)	LF (strict)	LF (broad)	LF (broad)	Unemployed (strict)	Unemployed (strict)	Unemployed (broad)	Unemployed (broad)
MEPI	-0.015	-0.006	-0.012	-0.002	0.027**	0.031**	0.032**	0.033**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.015)	(0.013)	(0.015)
Constant	-1.183***	-0.725**	-1.201***	-0.459	0.815***	0.575	0.978***	0.893**
	(0.040)	(0.335)	(0.038)	(0.331)	(0.056)	(0.448)	(0.055)	(0.452)
Observations	45,385	45,385	45,385	45,385	22,982	22,982	24,396	24,396
Number of pid		12,257		12,257		8,545		8,781

*Notes: For the full regression results, please see Appendix L. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017

Following previous authors (Churchill et al., 2021; Cheng et al., 2021), I employ the 2SLS model to account for endogeneity associated with household MEP. The findings show that household MEP is reported to have adverse effects on labour market outcomes. In Table 17, the results from the 2SLS model are consistent with those in Table 16. However, given the downward bias in the estimates (Nie et al., 2020; Awaworyi Churchill et al., 2020), the magnitude and significance of the FE-2SLS model's coefficients increase.[34] The results show that, significant at the 1% level, it is less probable that individuals living in MEP will participate in the labour force, according to the strict (19.50%) and broad (23.50%) definitions. Similarly, individuals living in MEP are 51% and 47% more likely to be unemployed, according to the strict and broad definitions respectively, than their non-energy poor counterparts. The results in Table 17 are all significant at the 1% level. In general, these estimates support the hypothesis that MEP renders an individual less active in the labour market (Dinkelman, 2011; Rathi & Vermaak, 2018). This might be explained by virtue of the fact that energy poor households are deprived of knowledge and information provided by television, internet and mobile phones,

[34] The magnitude of the coefficients increase by a large amount, which may raise the concern that, despite passing the relevant IV diagnostics, the IVs are in fact weak (Kahouli, 2020). Authors propose implementing the LIML estimator or utilising Lewbel's (2012) internally-generated instruments (Churchill & Smyth, 2020; Rafi et al., 2021) ; however, these techniques are beyond the scope of this paper.

hampering both the ability to upskill themselves and locate information about job opportunities (Sambodo & Novandra, 2019; Day et al., 2016).

Table 17 Labour Market Outcomes: FE-2SLS

	(1)	(2)	(3)	(4)
	LF (strict)	**LF (broad)**	**Unemployed (strict)**	**Unemployed (broad)**
MEPI	-0.195***	-0.235***	0.514***	0.470***
	(0.057)	(0.058)	(0.100)	(0.094)
Observations	44,126	44,126	20,712	22,225
Number of pid	10,998	10,998	6,275	6,61

*Notes: For the full regression results, please see Appendix L. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

Regarding the interplay of MEP and gender, Table 18, columns 1-4, exhibits that women are less likely to form part of the labour market if they reside in a household that is multidimensionally energy poor. The finding is significant at the 1% level and supports the hypothesis that women are at a greater disadvantage as they might be more dedicated to time-consuming domestic activities that stem from MEP (Grogan & Sadanand, 2013). Interestingly, males in MEP, however, face a marginally greater probability of being unemployed than females. This effect is analogous to that observed by Dinkelman (2011) whereby, in the wake of household electrification, males' employment rose to a lesser extent than females in rural KwaZulu-Natal.

Table 18 Labour Market Outcomes by gender: FE-2SLS

	(1-Female)	(2-Male)	(3-Female)	(4- Male)	(5-Female)	(6-Male)	(7-Female)	(8-Male)
	LF (strict)	**LF (strict)**	**LF (broad)**	**LF (broad)**	**Unemployed (strict)**	**Unemployed (strict)**	**Unemployed (broad)**	**Unemployed (broad)**
MEPI	-0.239***	-0.145	-0.277***	-0.188**	0.468***	0.512***	0.415***	0.495***
	(0.072)	(0.092)	(0.072)	(0.092)	(0.154)	(0.128)	(0.139)	(0.124)
Observations	26,238	17,888	26,238	17,888	11,225	9,487	12,284	9,941
Number of pid	6,293	4,705	6,293	4,705	3,429	2,846	3,668	2,942

*Notes: Refer to Appendix N for the full regression results. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

5.3. Child Outcomes

This section highlights the implications MEP has on human capital development outcomes amongst children. I use proxy education outcomes, such as the years of education a child has attained and the number of school days a child misses in 30 days. The sample is restricted to school-aged children: children aged 6 to 18 years old, namely the standard school-going age of children in South Africa[35]. I use a set of individual and household covariates that have been previously used in energy poverty-education literature – which includes age, age-squared, gender, household size, household income, whether there is a dependent in the household, mother's employment status, mother's education status, access to piped water, access to sanitation, area type and province (Karim et al., 2018; Rafi et al., 2021).

The estimated pooled OLS and FE regressions and 2SLS results of the outcomes of interest are reported in Table 19 and Table 20 respectively. The results in Table 19 suggest that MEP has significantly adverse effects on a child's education prospects: a child in energy poverty is more likely miss more school days than those children not in energy poverty. However, the significance attached to the FE results drops in comparison to the pooled OLS coefficients.

Table 19 Child Outcomes: Pooled OLS and Panel FE Results

	(1-OLS)	(2- FE)	(3-OLS)	(4-FE)	(5-OLS)	(6-FE)
	Years of school	**Years of school**	**School days missed**	**School days missed**	**School missed dummy**	**School missed dummy**
MEPI	-0.293***	0.043	0.286*	0.197	0.078***	0.060***
	(0.051)	(0.057)	(0.149)	(0.189)	(0.015)	(0.019)
Constant	-8.323***	1.305	1.483	-0.079	1.515***	2.417***
	(0.258)	(0.900)	(1.257)	(3.286)	(0.073)	(0.345)
Observations	12,975	12,975	8,127	8,127	13,092	13,092

[35] Children typically enroll in Grade 1 at ages 6-7 and finish Grade 12 at ages 18/19.

Number of pid		4,193		3,485		4,209

*Notes: For full regression results, refer to Appendix M. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

I now address the endogeneity concerns surrounding the MEP variable. Looking at Table 20, households where MEP is an issue, specifications in columns (2) and (3), indicate robust and significant effects of MEP on school years attained and the number of school days missed respectively. School-aged children residing in MEP households are expected to have 0.678 fewer years of schooling than their non-energy poor counterparts, significant at the 10% level. Furthermore, this MEP cohort miss 2.248 more days of school per month, on average. This estimate is significant at the 10% level. Overall, the findings from this section provide support for the theory that MEP has adverse effects on a human capital development, in this case, a child's schooling outcomes (Karim et al, 2018; Rafi et al., 2021; Zhang et al., 2021). It suggests that energy-poor households do perhaps fail to present an environment that is conducive to a child's learning, and thus educational achievements.

Table 20 Child Outcomes: FE-2SLS Results

	(1)	**(2)**	**(3)**
	Years of school	**Number of school days missed**	**School missed dummy**
MEPI	-0.678* (0.368)	2.248* (0.730)	-0.027 (0.129)
Observations	12,484	7,362	7,362
Number of pid	3,702	2,720	2,720

*Notes: For full regression results, refer to Appendix M. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017)

Interestingly, when differentiating by gender, as seen in Table 21, female children in MEP reportedly miss more days of school than male children in MEP. This result is significant at the 10% level. A female child living in MEP also faces a 41.70% higher chance (significant at the 5% level) of missing a day of school in comparison to those not in MEP, *ceteris paribus*. These effects are smaller and insignificant for their male counterparts. School-going girls may

spend more time assisting their mothers with household chores, such as collecting firewood or cooking, which may divert time away from their educational pursuits. This might result in fatigue that prevents them from attending school as shown in previous studies (Sovacool & Drupady, 2012; Heltberg, 2005).

Table 21 Child Outcomes by gender: 2SLS

	(1-Female)	(2- Male)	(3-Female)	(4-Male)	(5-Female)	(6-Male)
	Years of school	**Years of school**	**School days missed**	**School days missed**	**School missed dummy**	**School missed dummy**
MEPI	-0.755 (0.560)	-0.144 (0.490)	3.246* (1.660)	1.645 (1.959)	0.417** (0.200)	-0.167 (0.177)
Observations	5,163	5,191	3,029	3,012	5,218	5,235
Number of pid	1,525	1,55	1,113	1,121	1,536	1,559

*Notes: Refer to Appendix N for the full regression results. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001)*
Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017

5.4. Discussion

The results presented in Chapter 5 suggest that household energy poverty, with regards to the MEP, has adverse welfare implications for both adult and child individuals. The results support the theoretical foundation promulgated in 2.3.1. which highlights how lack of modern energy sources works has implications for an individual's secondary and basic capabilities. Overall, the findings agreed with prior literature looking at energy poverty-welfare models.

Regarding individual health outcomes, the results suggest an adverse association between energy poverty and mental health. Lower mental health statuses may have arisen due to physical burdens (Reddy et al., 2000); stress related to safety (Spengler et al., 2012); inability to adapt to temperatures; and feelings of social isolation (Lin & Okyere, 2020). The effect of energy poverty also extends to an individual's weight. This outcome may be interlinked with the adverse mental health outcomes energy poverty presents. As noted in previous literature, anxiety and stress may lead to overeating, interruption of sleep, and lowering of physical activity (Prakash & Munyanyi, 2021). As a robustness check, I found that MEP does not have

as dire implications for the undernourishment of children, as captured by the 'stunting' variable'. Furthermore, household energy poverty affects an adult individual's labour market outcomes. The results were generally highly significant, suggesting that energy poverty, on average, substantially decreased an individual's probability of being employed and participating in the labour market.

Lastly, energy poverty has a profound influence on a child's education. An immediate effect of household energy poverty is to increase the number of school days a child will miss. This effect is more pronounced for female children. I further observed that a child that experiences energy poverty is expected to attain 0.678 years less of schooling, on average, compared to those children not in energy poverty. Access to modern energy, such as electricity for lighting, may increase a child's study hours, and thus chances to attend and perform well in school. Better school performance can result in more years of education (Khandker et al., 2012).

The effects of MEP are gendered. For instance, women are often expected to use fuelwood for cooking, despite electrification. The costs and difficulties associated with energy poverty can therefore become a women's problem (Chipango, 2021). The results indicate that, when in energy poverty, women are less likely to participate in the labour market. Energy poor women are often involved in time-consuming household chores due to the use of traditional, inefficient energy technologies, thus leaving them less able to pursue employment activities (Dinkelman, 2011). This discussion might explain why the results also indicate a higher chance of depression in women.

5.5. Sensitivity Analysis

As relayed in the literature review, 'energy poverty' lacks a consensual definition (Pachauri & Spreng, 2011). Gaging energy poverty is made difficult by demonstrating its different dimensions and understanding the context in which these dimensions present themselves (Rafi et al., 2021). It is therefore important to consider more than one measure of energy poverty. To elucidate the implications energy poverty has on human wellbeing and how it feeds into policy insights, I consider alternative energy poverty definitions and measures.

Firstly, I regard a wholly different energy poverty measure – namely the Ten Percent Threshold indicator, which is adopted in some studies (Awaworyi Churchill & Smyth 2020; Barnes et al. 2011; Boardman 1991; Bouzarovski & Petrova 2015). As presented in literature, this measure intends to capture the affordability of adequate energy services. However, it is noted that the

TPT does not capture the multi-dimensional nature of energy poverty and therefore may not be suitable for developing nations (Day et al., 2016).

Table 22 captures the FE-2SLS regression results using the TPT as the main regressor of interest. On the whole, the results are consistent with the initial findings, pointing to the adverse effects energy poverty, even in its uni-dimensional form, has on human development outcomes. However, there are a number of departures necessary to highlight. In contrast to the MEPI, adult individuals living in TPT energy poverty show higher chances of being depressed, *ceteris paribus*. Likewise, there is a greater likelihood that an adult individual residing in energy poverty, according to the TPT, does participate in the labour force compared to the results using the MEPI. One interesting result pertains to the child stunting variable: children residing in households that are energy-poor according to this metric are 11.5% more likely to be stunted in comparison to their non-energy poor counter parts. One reason for the difference in esimates might be because, in line with prior literature, energy poverty effects are stronger when the metric contains a subjective element (Kahouli, 2020; Awaworyi Churchill et al., 2020; Prakash & Munyanyi, 2021). Furthermore, based on the construction of the TPT, higher energy expenditures may redirect household income away from expenditure on food (Khandker et al., 2012), for instance, and would explain the higher likelihood of a child being stunted.

Table 22 FE-2SLS Regression Results using the TPT

Health Outcomes				
	(1)	(2)	(3)	(4)
	Satisfied	Depressed	Overweight	Health index
TPT	-0.233***	0.126**	-0.043	-0.739***
	(0.062)	(0.053)	(0.040)	(0.206)
Observations	47,268	47,268	45,134	47,268
Number of pid	11,469	11,469	11,356	11,469
Labour Market Outcomes				
	(5)	(6)	(7)	(8)
	LF (strict)	LF (broad)	Unemployed (strict)	Unemployed (broad)
TPT	-0.317***	-0.313***	0.820***	0.811***
	(0.051)	(0.051)	(0.084)	(0.080)
Observations	44,126	44,126	20,712	22,225
Number of pid	10,998	10,998	6,275	6,61
Child Outcomes				
	(1)	(2)	(3)	(4)
	Stunting	Years of education	Number of school days missed	School missed dummy
TPT	0.115*	-0.144	1.378*	-0.076
	(0.069)	(0.252)	(0.744)	(0.097)
Observations	10,597	12,638	7,422	12,78
Number of pid	3,065	3,754	2,746	3,778

*Notes: Refer to Appendix O for the full regression results. Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017

Secondly, despite being regarded as a robust measure of energy poverty, the technical construction and availability of micro-data necessary for the MEPI faces controversy. As a further robustness check, I employ alternative weights[36] and an alternate threshold when constructing the multi-dimensional energy poverty variable. Previous literature cautions that the relative importance of each dimension used in the MEPI's construction may lead to variations in the results (Israel-Akinbo et al., 2018). With reference to the table in Appendix P, it is evident that effects are mostly consistent, in terms of size and magnitude, to the findings based on Nussbaumer et al.'s (2012) construction of the MEPI. However, the MEPI with a threshold of 0.2 indicates larger effects, albeit in the same direction, to those from the initial findings. In contrast to Nussabaumer et al. (2012), the results are marginally sensitive to a decrease in the cut-off.

5.6. Study Limitations

NIDS is a nationally representative dataset which offered a large sample size for this investigation and the necessary variables to construct both energy poverty indicators and outcome variables. However, a number of limitations were identified in the research, although their effects have mostly been mitigated as discussed in Chapter 4.

Firstly, it is important to acknowledge the possible bias and unmeasured confounders that stem from the research design, despite some bias being corrected for by the panel FE-approach and instrumental variables. Indicators, such as the household's surface (in square meters), the extent of indoor ventilation and seasonal variation in temperature at a district-level, have direct effects on EP and development outcomes (Prakash & Munyanyi, 2021). However, these variables are not captured in the NIDS dataset, thus resulting in potential omitted variable bias. Further research could also consider the how individuals are heterogenous across risk of depression, life satisfaction and other development outcomes. Energy poverty could therefore impact different individuals on varying scales based on their predispositions (Zhang et al., 2022).

[36] Please refer to Appendix A

The data availability did dictate the choice of EP metric. Lack of data to inform energy poverty metrics is not uncommon in research (Sovacool & Dworkin, 2015). In other words, I was not able to test EP metrics such as the LIHC indicator (whereby energy prices and household energy requirements are needed) demand-side indicators or subjective perceptions on household energy poverty. The NIDS dataset does not include information on household electricity consumption and whether the household uses prepaid or conventional metering.

Furthermore, I had to utilise the NERSA approved municipal tariffs from 2008 to 2017; however, there were notable gaps in the electricity price information available which could result in measurement errors. It is proposed that further research studying the energy poverty-human welfare nexus utilises a robust dataset of energy prices. Future studies could also implement techniques, such as Lewbel's (2012) 2SLS approach, to mitigate the effects of weak instruments.

Lastly, in the context of South Africa's 'load-shedding', the question of reliability and efficiency of energy sources also comes into play. As indicated by Khandker et al. (2012), power outages and voltage fluctuations that could cause losses in income and productivity. Further research could assess whether 'load-shedding' has implications for the welfare of individuals in South Africa.

Chapter 6. Concluding Remarks

This research paper intended to contribute to an enhanced understanding of the complex relationship between human development outcomes, namely in the health, child education, and labour market domains, and energy poverty in South Africa. The years preceding South Africa's democratisation saw substantial policy efforts in addressing the unequal access to electricity. Despite improvements in modern energy access over the years 2008 to 2017, energy poverty in South Africa is still prevalent. These numbers increase drastically when regarding rural areas, which can be attributed to the remnants of South Africa's Apartheid regime. In light of this, there is limited evidence in South Africa to date showing the effects of household energy poverty, in its multidimensional form, on human development outcomes. This study contributed to the literature on the influence energy poverty has on health, labour market and human development indicators in South Africa, using all five waves of the nationally representative NIDS panel dataset.

There is no agreed energy poverty indicator in policy and academia. Looking at previous studies, the second chapter of this study thus sought to find an appropriate indicator of energy poverty within the context of South Africa. Nusssbaumer et al.'s (2012) multi-dimensional poverty index (MEPI) was chosen due to its acceptance practice in energy poverty literature. The MEPI, underpinned by Sen's (1997) Capability Approach, seeks to view energy poverty as a multi-faceted issue of accessibility and affordability. Boardman's (1991) ten-percent threshold (TPT) is also adopted as a point of comparison. In Chapter 3, South Africa was shown to have high incidences of both forms, most notably in rural and lower income areas.

Through the use of empirical methods utilised in previous energy poverty literature were adopted, I was able to disentangle the effects of individual and household characteristics when determining the effects of energy poverty on human development outcomes. This was primarily achieved by using the FE approach, thus eliminating the issue of unobserved time-invariant variables, and employing electricity prices and the percentage of the population using biomass fuels as instruments to address the problem of endogeneity in pooled OLS and FE model(s). The coefficient on MEP is stronger and indicates greater statistical significance in the FE-2SLS estimates in comparison to both the OLS and FE models, which indicates that electricity prices

and the percentage of the population using biomass as a fuel source are strong barriers to human development.

When analysing the effect of energy poverty using the FE-2SLS model(s), and in line with prior literature, I showed energy poverty has adverse effects on human development outcomes. Energy poverty in its multidimensional form also burdens females different ways than it does to their male counterparts. One reason is that females are tasked with the burden of household chores, which, in energy poor households, involving the arduous collection and use of biomass fuels.

Household energy poverty Looking at the FE-2SLS model with regards to adult health outcomes, household energy poverty has severe effects on life satisfaction, depression and being overweight (for males). All of these estimates were highly significant. This is likely because energy poverty can be linked to socio-economic burdens that rest on adult individuals. The estimates in the overall FE-2SLS model pertaining to labour outcomes were also highly significant, revealing that adult individuals are both more likely to be unemployed and participate in the labour market if they reside in MEP households.

Another crucial finding points to the negative influence of household MEP on a child's education. This paper discovered that children in MEP households miss more days of school a month than their non-energy poor counterparts. They are also shown to attain proportionally less years of school. Although not MEP does not seem to effect a child's health, there is higher incidence of stunting amongst children in households that are energy poor according to the TPT.

Based upon these findings, it is evident that policymakers need to consider the role access to clean, modern energy has in promoting human development. Despite South African government's attempt to address access to affordable energy sources, these efforts have been insufficient. There is an urgent need for government to take serious steps to reach SDG 7, whilst also keeping in mind the interlinking concerns of the climate change, poverty and inequality. The following insights can inform policy decisions aimed at eradicating the negative effects of household energy poverty can be considered by the South African government:

- Assessing the extent to which energy poverty impacts individuals may assist policymakers identify energy poor households and address ways of improving social welfare. It is essential that policy adopts measure(s) of energy poverty that fit the social, historical and economic context of a country. For instance, in a country where income

inequalities and infrastructure inequity are high, such as South Africa, it is useful to utilise a measure that can be decomposed to offer granular insights to inform policy (Nussbaumer et al., 2012). The DoE and other government bodies should adopt a standardized and suitable metric to capture the energy poverty situation in South Africa. This will enable an analysis of energy poverty a regular basis. The MEPI has been widely used in other African countries (Halkos & Gkampoura, 2021). It is lauded for placing energy services at the centre of the metric. The metric also allows for decomposition analysis to a large extent (Crenstil et al., 2019; Israel-Akinbo et al., 2018). Based on both the reasons for use and the depth of insight provided by the MEPI in this paper, and prior literature, I recommend that policy should incorporate the use of the MEPI to capture South Africa's energy poverty situation.

- To reduce energy poverty and improve welfare, policymakers must regard a holistic approach in solving energy policy, where attention is paid to all the dimensions of MEP. For instance, the widespread reliance on biomass fuels for cooking and lighting purposes is only one dimension policy can target. The South African government can implement training and educational programmes targeted at households on energy-saving and the use of clean energy sources. It is necessary to confront the underlying processes and behaviours that give rise to the problems associated energy poverty (Chipango, 2021; Jayasinghe et al., 2021). In other words, individuals must be educated about the health and economic benefits of clean cooking fuels to increase their overall welfare, particularly for women involved in domestic work. South Africa's DoE and local municipalities are vital players in raising awareness in this regard. Furthermore, in light of the effect of recent COVID-19 pandemic and its associated lockdowns on education hindrances, policy should look to provide access to computers, internet and mobile phones because they can play a greater role in assisting adolescents attain an adequate education (Jayasinghe et al., 2021).
- Lastly, policymakers need to strengthen the supply of clean energy services in order to alleviate energy poverty (Dong et al., 2021). Gregory & Sovacool (2019) point out that modern energy access in Sub-Saharan Africa is an issue of finance. Access to modern forms of energy mostly exists due to enabling infrastructure, which requires investment in energy facilities, such as power grid upgradation; gas pipeline construction and energy equipment maintenance (Zhang et al., 2022). Recent thinking in the multilateral development space communicates the need for a country to "relinquish their utility's

monopoly control" (Gregory & Sovacool, 2019: pg. 353). It is further urged that stakeholders rely on a mixture of private investment and decentralised electricity services to provide adoption of new technologies and electricity delivery solutions. For example, the South African government could promote private sector involvement with Energising Development (EnDev) programmes, a results-based financing[37] approach targeted to enhance energy access markets. Furthermore, in light of the recent 2021 United Nations Climate Change Conference (also known as COP26), transition to innovative and greener forms of renewable energy sources, such as Tanzania's Solar Sister social enterprise, could further cushion the shocks of energy poverty (Gray et al., 2018; Adom et al., 2021). This is especially in the context of South Africa's unreliable and exorbitantly priced energy sources. With greater supply of clean, renewable energy sources, energy poor households could afford to move away from traditional biomass (Dong et al., 2021). Based on these findings, I urge government figures to hasten the transition towards low-carbon, clean energy sources to alleviate household energy poverty.

Overall, policy design should be made with the local context and preferences in mind and should emphasise household economic and behavioural factors that influence a household's energy choice. It is important that the South African government adopts a suitable metric to capture the energy poverty situation , especially at a household level. The frequent analysis of energy poverty trends will enable the government to assess the effectiveness of investing into energy infrastructure.

[37] Results-based financing (RBF) is "a mechanism whereby a donor disburses funds to a recipient once a pre-agreed set of results has been achieved" (EnDev, 2018).

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Appendix

A. Alternative MEPI derivations

Table 23 MEPI dimension weights according to Israel-Akinbo et al. (2018)

Dimension	Indicator (weight)	Variables	Energy poor if…
Cooking	Modern cooking fuel (0.3)	Type of cooking fuel	Energy source is not electricity (or generator), LPG or solar
Lighting	Modern energy lighting (0.35)	Type of energy source used for lighting	Using any energy source beside electricity (or a generator), LPG or solar

Ownership of asset	Household appliance ownership (0.15)	Has freezer / fridge	False
	Ownership of entertainment or education appliance (0.15)	Has radio / television / computer	False
Heating	Modern heating fuel (0.05)	Type of heating fuel	Use any fuel beside electricity (or generator), LPG or solar

Table 24 MEPI dimension weights according to Mendosa et al. (2019)

Dimension	Indicator (weight)	Variables	Energy poor if…
Cooking	Modern fuel (0.2)	Type of cooking fuel	Primary source of cooking fuel is biomass
	Indoor pollution (0.2)	Type of stove used for cooking	Stove is not electric or gas
Lighting	Electricity access (0.2)	Household is connected to national grid	False
Ownership of asset	Household appliance ownership (0.1)	Has freezer / fridge	False
	Ownership of entertainment or education appliance (0.2)	Has radio / television / computer	False
Heating	Modern heating fuel (0.1)	Type of heating fuel	Use any fuel beside electricity (or generator), LPG or solar

Table 25 Comparison of MEP indicators

Source	**Headcount ratio (H)**	**Intensity (A)**	**Adjusted Headcount Ratio (M0)**
Nussbaumer et al. (2012) and Le Roux & Chourmet (2021)	0.228 (0.015)	0.690 (0.012)	0.157 (0.011)
Israel-Akinbo et al. (2018)	0.264 (0.017)	0.707 (0.016)	0.187 (0.014)
Mendosa et al. (2019)	0.308 (0.016)	0.683 (0.013)	0.210 (0.014)

Note: Standard error in brackets. Stata's mpi was used to calculate the estimates shown in the above table (Pacifco & Poege, 2017). Estimates are weighted using wave 5 panel weights and complex survey design elements are accounted for.

Source: Author's own calculations using NIDS data from SALDRU (2008; 2010; 2012; 2015; 2017).

B. MEPI Headcount Ratio, Intensity and Adjusted Headcount

The following calculation is from the work of Alkire and Foster (2011) and subsequently adapted by Nussbaumer et al. (2012).

The Headcount Ratio (H) indicates the share of the population in energy poverty. This is shown as:

$$H = q/n$$

Where H is the headcount ratio, n refers to the total population and q refers to the number of energy-poor households. To calculate the Intensity (A), the average percentage of simultaneous deprivations suffered by energy poor households, the following calculation is used:

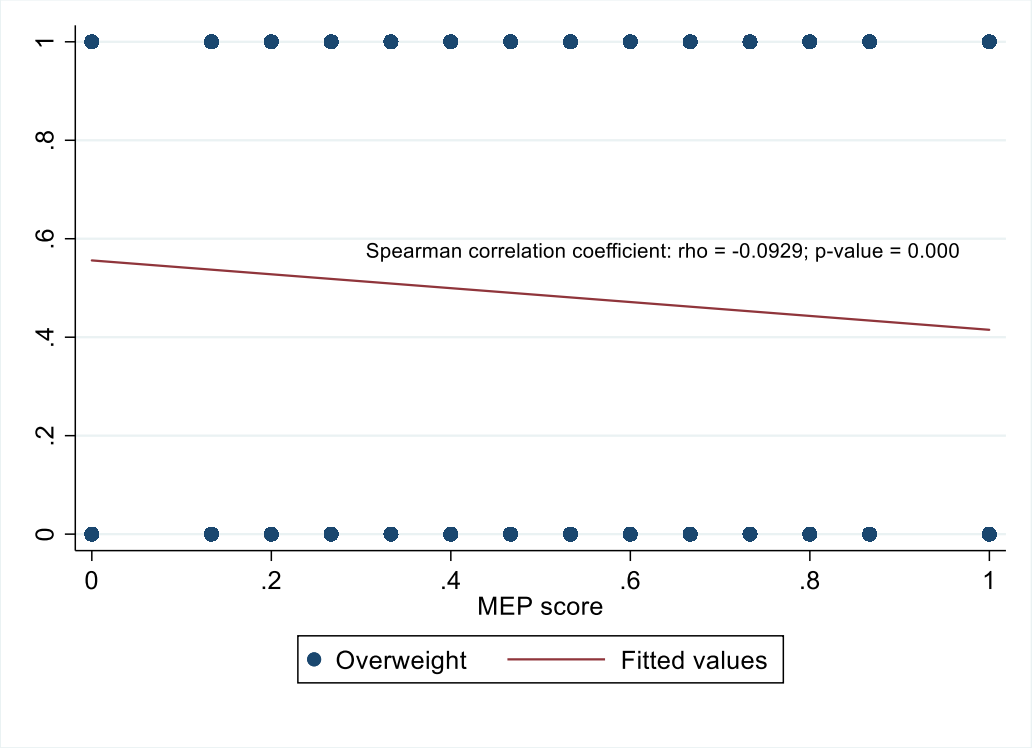
$$A = \sum_{i=1}^{n} DS_i(k)\,/q$$

Here, $DS_i(k)$ pertains to the count of household *i*'s multidimensional energy deprivations. Lastly, to calculate multidimensional poverty, one finds the product of the headcount ratio and energy poverty intensity:

$$M = H * A = \frac{\sum_{i=1}^{n} DS_i(k)}{n}$$

C. Preliminary associations between MEP and Health outcome variables

Figure 7 Scatterplot indicating the association between being overweight and MEP score for individuals older than 16



D. Hausman Test Results

Table 26 Hausman Test Results: FE or RE

Model	Chi2	Prob>Chi2	RE or FE
Model 1: Life satisfaction	101.91	0.000	FE
Model 2: Depressed	67.25	0.000	FE
Model 3: Objective health	146.10	0.000	FE
Model 4: Overweight	110.70	0.000	FE
Model 5: Child stunting	35.03	0.02	FE
Model 6: Child school years	1113.14	0.000	FE
Model 7: Unemployed (broad)	142.65	0.000	FE
Model 8: Labour force participant (broad)	722.17	0.000	FE

E. Appendix: Transition matrix of outcome variables

Table 27 Transition Matrix: Outcome Variables

Wave t-1	Wave t		
	Positive (=0)	**Negative (=1)**	**Total**
(a.) Life satisfaction			
Satisfied (=0)	37,00	63,00	100
Not satisfied (=1)	20,46	79,m4	100
(b.) Depressed			
Depressed (=0)	71.08	28.92	100
Not Depressed (=1)	66.98	33.02	100
(c.) Bad health condition			
Bad Health (=0)	81,31	18,68	100
No bad health (=1)	64,97	35,03	100
(d.) Overweight			
Overweight (=0)	84,51	15,49	100
Not overweight (=1)	17,80	8,22	100
(e.) Child stunting			
Stunted (=0)	89,72	10,28	100
Not stunted (=1)	50,22	49,77	100
(f.) School day missed			
Missed school (=0)	51.89	48.11	100
Did not miss school (=1)	36.03	63.97	100
(g.) Unemployed (broad)			
Unemployed (=0)	84,82	15,18	100
Not unemployed (=1)	51,45	48,55	100
(h.) Labour force participant (broad)			
Labour force participant (=0)	69,32	30,68	100
Not labour force participant (=1)	29,33	70,76	100

F. Strict Exogeneity Test Results

a.) Multidimensional Energy Poverty Index:

Model	C-statistic	Endogeneity present
Model 1: Life satisfaction	5.308**	Yes
Model 2: Depressed	7.530***	Yes
Model 3: Overweight	8.622***	Yes
Model 4: Bad health	19.809***	Yes
Model 4: Child stunting	22.370***	Yes
Model 5: Number of school days missed (child)	3.324**	Yes
Model 6: Unemployed (broad)	11.454***	Yes
Model 7: Labour force participant (broad)	128.106***	Yes

b.) Ten Percent Threshold Index:

Model	C-statistic	Endogeneity present
Model 1: Life satisfaction	5.813**	Yes
Model 2: Depressed	7.166***	Yes
Model 3: Overweight	11.302***	Yes
Model 4: Bad health	26.884***	Yes
Model 4: Child stunting	3.112*	Yes
Model 5: Number of school days missed (child)	3.651**	Yes
Model 6: Unemployed (broad)	177.129***	Yes
Model 7: Labour force participant (broad)	103.115***	Yes

G. List of Potential IVs

Variable	F-statistic (First-stage)	Coefficient (First-stage)
Access to piped water	63.03	0.040***
Share of population in MEPI in district	1678.07	0.009***
Share of population using biomass in province	386.75	0.007***
Log of household electricity expenditure	164.76	-0.041***

H. Summary of share of population using biomass as a fuel source by wave

		Share of population using biomass	Share of population not using biomass	Total
Wave 1	*Total*	3,738	11,965	15,703
	%	18.13	81.87	100
Wave 2	*Total*	3,151	12,552	15,703
	%	14.79	85.21	100
Wave 3	*Total*	2,481	13,222	15,703
	%	11.45	88.55	100
Wave 4	*Total*	1,996	13,707	15,703
	%	9.89	90.11	100
Wave 5	*Total*	1,269	14,434	15,703
	%	6.07	93.93	100

Notes: Percentage reported is weighted. Count numbers represent the unweighted sample.

I. Electricity Price IV construction

The panel dataset utilised is at the individual/ wave level as there is just one development indicator datapoint per respondent per wave. However, despite including a variable documenting the household monthly electricity expenditure, the NIDS longitudinal dataset does not contain information on electricity prices. I therefore had to utilise the information made available by NERSA's approved local municipal electricity tariffs for the respective waves.

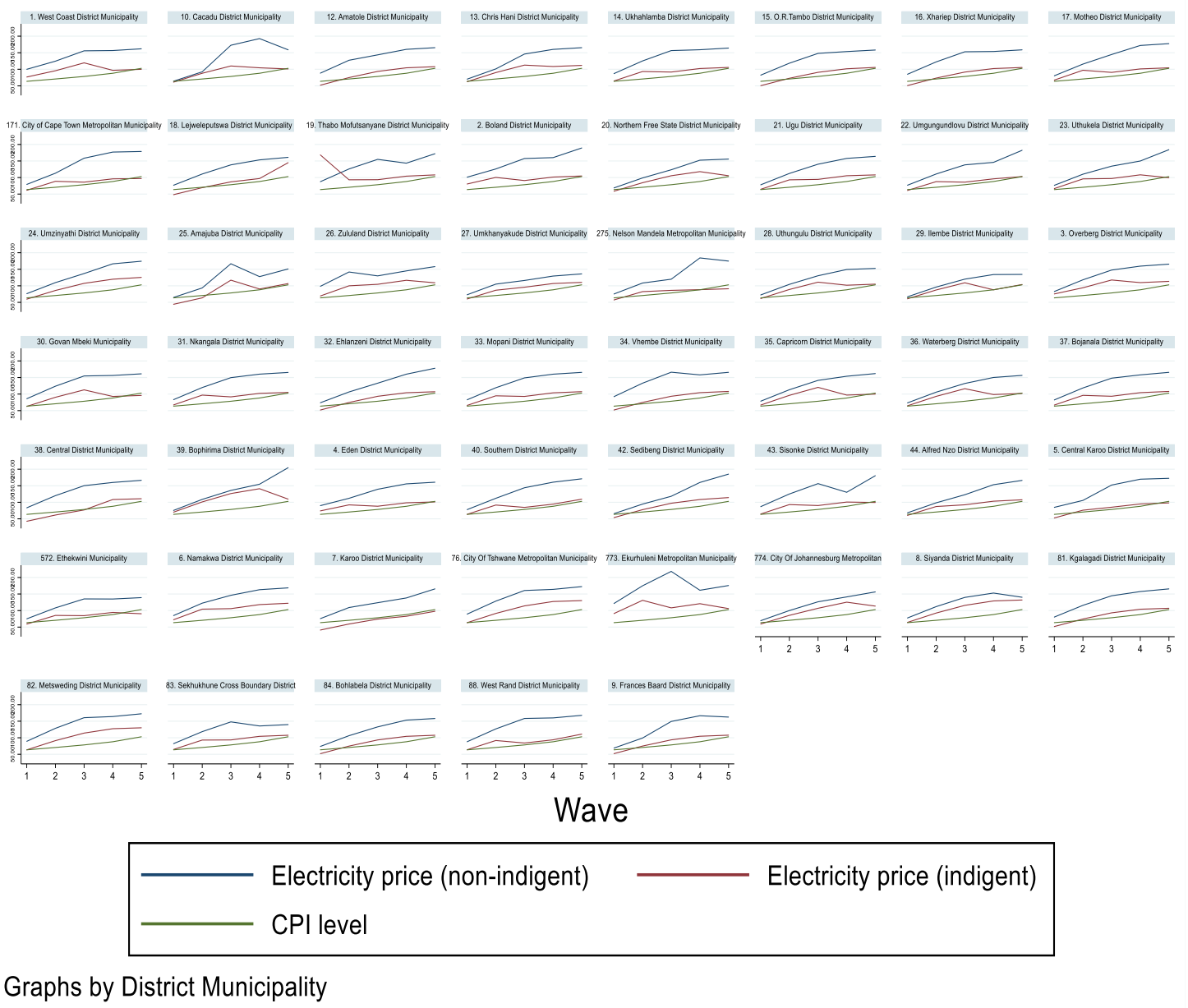
There were a number of limitations encountered when pursuing this direction that undoubtedly affects the accuracy of the electricity price variable, resulting in probable measurement error issues. The restriction in the price data make the accurate analysis of energy poverty facing different tariff rates impossible. Firstly, there was the difficulty in determining the average price faced by the household since Inclining Block Tariffs (IBTs) were introduced by NERSA in 2010, thus one could not determine the average price faced by the household given their level of expenditure. Therefore, I assumed that indigent households would fall into the cheapest option available. Other households were given a weighted average of the other conventional tariff rates available (including Block 3 and Block 4). This is underpinned by the assumption that households do not readily switch their tariff options, as this is costly and inconvenient (Anderson, 2004). Furthermore, NERSA only released electricity tariff data for local municipalities; however, the NIDS dataset differentiates municipalities at the district municipal level. To accommodate this, I averaged the local municipal electricity tariff across all local

municipalities to get a representative tariff for the district municipality. Thirdly, NERSA's website provides documentation on the approved tariff rates for the years 2016/2017, 2015 and 2010. It was necessary to fill in the missing data gaps by applying ESKOM's average domestic electricity price increase, although the municipalities set their own percentage increases which is approved by NERSA. The nominal electricity prices were then adjusted for inflation to reflect the 2017 (wave 5) prices.

Lastly, South Africa's FBE policy stipulates that 'indigent' households, identified by the local municipality, will receive a maximum of 50kWh – 60kWh per household per month (Department of Minerals and Energy, 1998). 'Indigent' households receive a separate tariff that is lower than the conventional/ prepaid tariff rates. The NIDS dataset does not indicate whether a household is registered on the National Indigent Database. However, based on the data provided by StatsSA's non-financial census of South African municipalities, I was able to determine which households in the NIDS dataset would be considered 'indigent' by each municipality based on their monthly income and whether the income is above or below an income threshold. The indigent income thresholds differ per municipality based on the resources available for the municipality to allocate to these groups (StatsSA 2008; 2010; 2012; 2015; 2017). I therefore assigned the indigent tariff to households considered indigent according to this specification; there are 28,530 households in the NIDS dataset that could be considered indigent. Although it is acknowledged that there are other criteria required for a household to meet to be considered 'indigent', household income was the only method available based on the dataset at hand.

I match the year in which the respondent was interviewed with the electricity price that year. Electricity prices are also matched according to the local district municipality, which the NIDS dataset provides data for. Effectively, the combination of the local district municipality and wave provides a unique identifier to enable the merging of the NIDS panel dataset and the electricity price data to take place. This method of attaching electricity prices to the relevant households should provide a good approximation of the electricity prices a household would face. Figure 8 below indicates the variations in electricity prices across the districts over time. Overall, the instruments contain variation across individuals, districts and time, which allows for causal inference.

Figure 8 Electricity price and CPI-level by district



J. First-stage regression results & IV Diagnostics

a.) Multidimensional Energy Poverty Index:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Life Satisfaction**	**Depressed**	**Over-weight**	**Health Index**	**LF (broad)**	**Unemployed (broad)**	**Stunted**	**School missed**
Electricity price	-0.078***	-0.078***	-0.078***	-0.078***	-0.074***	-0.074***	-0.080***	-0.085***
F-statistics	55.19***	55.19	55.19	55.19	40.88***	40.88***	11.83	9.05***
Share of district population using biomass	0.007***	0.007***	0.007***	0.007***	0.006***	0.006***	0.006***	0.006***
F-statistics	907.28	907.28	907.28	907.28	637.56	637.5	66.74	132.20
Observations	48,753	48,753	48,753	40,377	40,377	40,377	10,502	7,624

b.) Ten Percent Threshold:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Life Satisfaction**	**Depressed**	**Over-weight**	**Health Index**	**LF (broad)**	**Unemployed (broad)**	**Stunted**	**School missed**
Ln of electricity price	-0.357***	-0.357***	-0.357***	-0.357***	-0.368***	-0.368***	-0.353***	-0.384***
F-statistic	1100.81	1100.81***	1100.81***	1100.81***	936.15***	936.15***	224.83***	131.17
Share of district population using biomass	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0003***	-0.0003***	-0.001***	-0.001***
F-statistic	542.89	542.89	542.89	542.89	468.81	468.81	113.72	76.39
Observations	49,216	49,216	49,216	49,216	40,769	40,769	10,597	7,684

a.) Multidimensional Energy Poverty Index:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Life Satisfaction**	**Depressed**	**Over-weight**	**Health Index**	**LF (broad)**	**Unemployed (broad)**	**Stunted**	**School missed**
IV: Electricity Price								
Hansen J: Over-identification test	Equation is exactly identified							
Kleibergen-Paap LM: Under-	52.718***	52.750***	56.966***	52.750***	40.895***	24.459***	11.915***	9.046***

identification test								
Cragg-Donald Wald: Weak Identification	58.718***	58.718***	63.833***	58.718***	45.938***	28.275***	13.121**	10.543**
IV: Share of district population using biomass								
Hansen J: Over-identification test	3.082*	3.082*	3.082*	3.082*	3.082*	3.082*	4.993*	3.331*
Kleibergen-Paap LM: Under-identification test	803.625***	803.625***	732.510***	548.424***	418.646***	133.931***	86.446***	56.614***
Cragg-Donald Wald: Weak Identification test	583.252***	583.252***	535.562***	479.873***	376.401***	124.820***	70.810***	44.956***
Observations	46,835	46,835	46,835	46,835	40,377	40,377	10,597	7,684

b.) Ten Percent Threshold:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	**Life Satisfaction**	**Depressed**	**Over-weight**	**Health Index**	**LF (broad)**	**Unemployed (broad)**	**Stunted**	**School missed**
IV: Electricity Price								
Hansen J: Over-identification test	Equation is exactly identified							
Kleibergen-Paap LM: Under-identification test	1027.691***	52.750***	56.966***	52.750***	40.895***	24.459***	11.915***	9.046***
Cragg-Donald Wald: Weak Identification	725.589***	58.718***	63.833***	58.718***	45.938***	28.275***	13.121**	10.543**
IV: Share of district population using biomass								
Hansen J: Over-identification test	1.251	1.251	5.696*	4.230*	8.293**	2.511	1.167	6.501*
Kleibergen-Paap LM: Under-identification test	521.120***	521.120***	485.037***	521.120***	418.440***	368.949***	209.640***	127.236***
Cragg-Donald Wald: Weak Identification	762.449***	762.449***	723.918***	762.449***	654.929***	295.969***	148.488***	90.902***
Observations	46,835	46,835	46,835	46,835	40,377	40,377	10,597	7,684

K. Health Outcomes Regression Results

	OLS - Satisfied	FE- Satisfied	OLS - Depressed	FE- Depressed	OLS- Overweight	FE- Overweight	OLS- Health Index	FE- Health Index	2SLS - Satisfied	2SLS - Depressed	2SLS- Overweight	2SLS – Health Index
MEPI	-0.075***	-0.032***	0.018*	0.011	-0.063***	-0.016*	-0.028	-0.083**	-0.140**	-0.150***	0.088**	0.112
	(0.013)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.037)	(0.037)	(0.064)	(0.055)	(0.045)	(0.222)
Age	-0.009***	0.001	0.007***		0.026***	0.044***	0.029***	-0.154***	-0.006	-0.017*	0.042***	-0.143***
	(0.002)	(0.010)	(0.001)	(0.009)	(0.002)	(0.007)	(0.006)	(0.037)	(0.011)	(0.010)	(0.007)	(0.039)
Age2	0.000***	0.000	-0.000***	-0.000	-0.000***	-0.000***	-0.000	0.001***	0.000**	-0.000	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	0.013*		0.031***		0.250***		0.441***		-	-	-	-
	(0.008)		(0.006)		(0.013)		(0.033)					
Married dummy	0.073***	0.026*	-0.045***	-0.012	0.099***	0.043***	-0.042	0.043	0.027	-0.013	0.041***	0.054
	(0.012)	(0.016)	(0.007)	(0.013)	(0.013)	(0.013)	(0.033)	(0.056)	(0.016)	(0.014)	(0.013)	(0.061)
Not economically active	-0.032***	-0.037***	0.030***	0.028***	-0.042***	-0.011*	0.026	-0.143***	-0.039***	0.029***	-0.012*	-0.151***
	(0.010)	(0.010)	(0.008)	(0.008)	(0.009)	(0.006)	(0.036)	(0.030)	(0.010)	(0.008)	(0.007)	(0.033)
Dependent dummy	0.008	0.015	-0.004	-0.013	-0.001	0.009	-0.032	-0.044	0.012	-0.012	0.006	-0.032
	(0.010)	(0.013)	(0.009)	(0.012)	(0.010)	(0.008)	(0.038)	(0.048)	(0.013)	(0.012)	(0.008)	(0.047)
Household income per capita	0.000*	0.000*	-0.000**	-0.000	0.000**	0.000**	-0.000	0.000*	0.000	-0.000	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Years of Education	0.014***	-0.000	-0.004***	0.009**	0.012***	0.001	-0.059***	-0.015	0.001	0.006	0.000	-0.014
	(0.001)	(0.004)	(0.001)	(0.004)	(0.002)	(0.003)	(0.006)	(0.020)	(0.005)	(0.004)	(0.003)	(0.017)
Smoke dummy	-0.023**	-0.009	0.023**	0.007	-0.179***	-0.059***	0.165***	0.220***	0.002	0.009	-0.054***	0.223***
	(0.011)	(0.018)	(0.010)	(0.016)	(0.015)	(0.014)	(0.048)	(0.061)	(0.019)	(0.017)	(0.013)	(0.067)
Household size	-0.003	-0.000	-0.000	-0.000	0.000	-0.000	0.002	-0.000	-0.001	0.000	0.001	-0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.005)	(0.007)	(0.002)	(0.002)	(0.001)	(0.007)
Piped water dummy	-0.017	0.025**	0.001	-0.005	-0.018**	0.001	0.142***	0.089***	0.028**	-0.004	-0.002	0.077**
	(0.021)	(0.011)	(0.008)	(0.009)	(0.009)	(0.007)	(0.038)	(0.033)	(0.011)	(0.010)	(0.007)	(0.037)
Dwelling type dummy	-0.079***	-0.067***	-0.006	-0.015	-0.011	-0.019*	0.037	0.024	-0.039*	-0.002	-0.035***	-0.013
	(0.022)	(0.018)	(0.013)	(0.015)	(0.013)	(0.011)	(0.078)	(0.059)	(0.021)	(0.017)	(0.013)	(0.069)
Area dummy	-0.003	0.014	0.013	0.009	0.024**	0.021	0.134***	0.002	-0.020	0.025	0.028	-0.019
	(0.018)	(0.025)	(0.010)	(0.022)	(0.011)	(0.019)	(0.043)	(0.087)	(0.025)	(0.022)	(0.020)	(0.081)

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).

L. Labour Market Outcomes Regression Results

	OLS- LF (strict)	FE- LF (strict)	OLS- LF (broad)	FE- LF (broad)	OLS – Unemployed (strict)	FE - Unemployed (strict)	OLS - Unemployed (broad)	FE- Unemployed (broad)	2SLS - LF (strict)	2SLS - LF (broad)	2SLS - Unemployed (strict)	2SLS - Unemployed (broad)
MEPI	-0.015	-0.006	-0.012	-0.002	0.027**	0.031**	0.032**	0.033**	-0.195***	-0.235***	0.514***	0.470***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.015)	(0.013)	(0.015)	(0.057)	(0.058)	(0.100)	(0.094)
Age	0.089***	0.079***	0.092***	0.068***	-0.028***	-0.030***	-0.032***	-0.044***	0.083***	0.071***	-0.026**	-0.040***
	(0.002)	(0.009)	(0.002)	(0.009)	(0.002)	(0.012)	(0.002)	(0.012)	(0.009)	(0.009)	(0.013)	(0.013)
Age2	-0.001***	-0.001***	-0.001***	-0.001***	0.000***	0.000***	0.000***	0.001***	-0.001***	-0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	-0.113***		-0.105***		0.084***		0.097***		-	-	-	-
	(0.009)		(0.009)		(0.009)		(0.010)					
Married dummy	-0.022*	-0.017	-0.024**	-0.018	-0.027***	0.025*	-0.024**	0.032**	-0.016	-0.019	0.006	0.012
	(0.012)	(0.012)	(0.011)	(0.012)	(0.010)	(0.015)	(0.010)	(0.015)	(0.013)	(0.013)	(0.017)	(0.016)
Dependent dummy	-0.035***	-0.017	-0.033***	-0.024**	0.050***	0.032**	0.052***	0.023	-0.026**	-0.034***	0.053***	0.041**
	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.015)	(0.012)	(0.015)	(0.012)	(0.012)	(0.017)	(0.016)
Household income per capita	0.000***	0.000***	0.000**	0.000***	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Years of Education	0.023***	0.025***	0.022***	0.035***	-0.002	0.004	-0.005***	0.006	0.024***	0.035***	0.004	0.006
	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.006)	(0.002)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)
Smoke dummy	0.036***	0.082***	0.035***	0.079***	0.003	-0.041**	-0.001	-0.054***	0.083***	0.079***	-0.063***	-0.071***
	(0.010)	(0.014)	(0.010)	(0.015)	(0.012)	(0.019)	(0.013)	(0.019)	(0.015)	(0.016)	(0.022)	(0.022)
Household size	-0.005***	-0.008***	-0.005**	-0.007***	0.011***	0.013***	0.012***	0.016***	-0.009***	-0.008***	0.014***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Piped water dummy	0.012	0.032***	0.015*	0.030***	0.034***	0.013	0.035***	0.008	0.039***	0.037***	0.000	-0.002
	(0.009)	(0.008)	(0.009)	(0.008)	(0.010)	(0.011)	(0.012)	(0.011)	(0.009)	(0.009)	(0.013)	(0.013)
Dwelling type dummy	0.068***	0.033**	0.064***	0.032**	0.002	0.014	-0.009	0.014	0.061***	0.062***	-0.035	-0.031
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.019)	(0.016)	(0.019)	(0.016)	(0.016)	(0.025)	(0.024)
Area dummy	0.037***	0.061***	0.030**	0.057***	-0.013	-0.042	-0.022*	-0.048	0.035*	0.028	-0.017	-0.022
	(0.012)	(0.020)	(0.012)	(0.019)	(0.012)	(0.030)	(0.013)	(0.031)	(0.020)	(0.020)	(0.030)	(0.029)

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).

M. Child Outcomes Regression Results

	OLS-Stunted	FE-Stunted	OLS-Education years	FE-Education years	OLS-Number of school days missed	FE-Number of school days missed	OLS-School missed dummy	FE-School missed dummy	2SLS-Stunted	2SLS-Education years	2SLS-Number of School days missed	2SLS-School missed dummy
MEPI	0.053***	0.005	-0.293***	0.043	0.286*	0.197	0.078***	0.060***	-0.090	-0.678*	2.248*	-0.027
	(0.017)	(0.015)	(0.051)	(0.057)	(0.149)	(0.189)	(0.015)	(0.019)	(0.090)	(0.368)	(1.255)	(0.129)
Age	-0.034***	-0.028**	1.231***	0.620***	-0.065	-0.015	-0.234***	-0.267***	-0.028**	0.617***	0.143	-0.273***
	(0.006)	(0.013)	(0.033)	(0.062)	(0.112)	(0.247)	(0.011)	(0.023)	(0.013)	(0.063)	(0.259)	(0.024)
Age2	0.002***	0.002***	-0.012***	-0.006***	0.002	0.006	0.012***	0.011***	0.002***	-0.005***	0.003	0.011***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.005)	(0.009)	(0.000)	(0.000)	(0.000)	(0.001)	(0.008)	(0.001)
Gender	-0.010		0.394***		-0.110		0.002		-	-	-	-
	(0.011)		(0.046)		(0.082)		(0.009)					
Dependent Dummy	-0.007	0.003	-0.203**	0.072	-0.673	-0.782	-0.131***	-0.241***	-0.006	0.064	-0.966	-0.242***
	(0.032)	(0.033)	(0.094)	(0.067)	(1.072)	(1.002)	(0.009)	(0.023)	(0.031)	(0.071)	(0.630)	(0.026)
Household size	0.005**	-0.001	-0.012*	-0.018*	0.000	-0.002	0.002	-0.002	-0.001	-0.015	-0.013	-0.003
	(0.002)	(0.002)	(0.007)	(0.010)	(0.019)	(0.031)	(0.002)	(0.004)	(0.003)	(0.011)	(0.036)	(0.004)
Household income per capita	-0.000**	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Mother employed dummy	-0.007	-0.004	0.032	0.014	-0.023	0.036	0.009	0.011	-0.007	0.002	0.136	0.012
	(0.012)	(0.012)	(0.042)	(0.045)	(0.101)	(0.106)	(0.011)	(0.016)	(0.012)	(0.048)	(0.115)	(0.018)
Mother education	-0.003		0.046***		-0.009		-0.004**		-	-	-	-
	(0.002)		(0.009)		(0.009)		(0.002)					
Piped water access	0.024**	-0.009	-0.089*	-0.016	0.044	0.061	-0.001	-0.000	-0.005	-0.007	0.047	0.000
	(0.011)	(0.012)	(0.049)	(0.051)	(0.116)	(0.132)	(0.018)	(0.019)	(0.013)	(0.056)	(0.144)	(0.020)
Area Dummy	0.015	0.028	-0.131**	-0.259*	0.292*	2.017	0.044***	-0.030	0.040	-0.465*	0.526	-0.081
	(0.018)	(0.031)	(0.060)	(0.141)	(0.169)	(1.761)	(0.016)	(0.078)	(0.041)	(0.247)	(0.552)	(0.064)

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).

N. Gender-disaggregated FE-2SLS Results

Health Outcomes

	(1) Female Satisfied	(2) Male Satisfied	(3) Female Depressed	(4) Male Depressed	(5) Female Overweight	(6) Male Overweight	(7) Female Health Index	(8) Male Health Index
MEPI	-0.108	-0.185	-0.126**	-0.159	-0.022	0.272***	0.104	0.140
	(0.073)	(0.118)	(0.064)	(0.100)	(0.051)	(0.082)	(0.267)	(0.384)
Married	0.029	0.030	0.002	-0.035	0.044***	0.028	0.079	0.019
	(0.019)	(0.030)	(0.016)	(0.026)	(0.015)	(0.023)	(0.070)	(0.112)
Not Economically Active	-0.026**	-0.060***	0.022**	0.040***	-0.006	-0.023*	-0.161***	-0.132**
	(0.012)	(0.019)	(0.011)	(0.014)	(0.008)	(0.013)	(0.041)	(0.054)
Dependent dummy	0.026	-0.000	-0.013	-0.009	-0.000	0.019	-0.028	-0.024
	(0.016)	(0.022)	(0.015)	(0.019)	(0.011)	(0.014)	(0.063)	(0.068)
Household income	0.000	0.000	-0.000	0.000	0.000	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education years	-0.002	0.005	0.007	0.005	0.010**	-0.006	-0.009	-0.016
	(0.006)	(0.007)	(0.006)	(0.006)	(0.004)	(0.005)	(0.024)	(0.025)
Smoke Dummy	0.020	-0.000	0.017	0.009	-0.027	-0.054***	0.376**	0.192***

	(0.030)	(0.023)	(0.033)	(0.020)	(0.021)	(0.016)	(0.184)	(0.068)
Household size	0.000	-0.004	0.000	0.001	0.001	0.001	0.004	-0.011
	(0.003)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)	(0.009)	(0.011)
Access to piped water	0.025*	0.033*	0.012	-0.025*	0.012	-0.020*	0.107**	0.040
	(0.014)	(0.019)	(0.012)	(0.015)	(0.009)	(0.012)	(0.051)	(0.054)
Dwelling type	-0.043*	-0.034	-0.017	0.012	0.000	-0.081***	0.028	-0.073
	(0.026)	(0.034)	(0.023)	(0.027)	(0.016)	(0.021)	(0.094)	(0.101)
Area type	-0.025	-0.022	0.024	0.027	0.019	0.037	-0.010	-0.020
	(0.032)	(0.040)	(0.029)	(0.034)	(0.024)	(0.031)	(0.116)	(0.114)

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).

Labour Market Outcomes

	(1) Female	**(2) Male**	**(3) Female**	**(4) Male**	**(5) Female**	**(6) Male**	**(7) Female**	**(8) Male**
	LF (strict)	**LF (strict)**	**LF (broad)**	**LF (broad0**	**Unemployed (strict)**	**Unemployed (strict)**	**Unemployed (broad)**	**Unemployed (broad)**
MEPI	-0.239***	-0.145	-0.277***	-0.188**	0.468***	0.512***	0.415***	0.495***
	(0.072)	(0.092)	(0.072)	(0.092)	(0.154)	(0.128)	(0.139)	(0.124)
Married	-0.028	0.007	-0.033*	0.006	0.052**	-0.047**	0.055**	-0.041*

	(0.018)	(0.020)	(0.017)	(0.021)	(0.024)	(0.023)	(0.023)	(0.023)
Dependent dummy	-0.020	-0.032*	-0.031**	-0.036*	0.042*	0.052**	0.021	0.052**
	(0.015)	(0.018)	(0.015)	(0.019)	(0.022)	(0.025)	(0.021)	(0.025)
Education years	0.021***	0.028***	0.035***	0.035***	0.006	0.003	0.012	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.010)	(0.008)	(0.010)	(0.008)
Smoke	0.086***	0.072***	0.087***	0.066***	-0.109**	-0.057**	-0.121**	-0.063***
	(0.032)	(0.018)	(0.033)	(0.018)	(0.054)	(0.024)	(0.052)	(0.024)
Household size	-0.007***	-0.013***	-0.005**	-0.012***	0.010**	0.023***	0.013***	0.026***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Access to piped water	0.032***	0.047***	0.034***	0.041***	-0.010	0.010	-0.009	0.004
	(0.012)	(0.014)	(0.012)	(0.014)	(0.018)	(0.018)	(0.018)	(0.018)
Dwelling type	0.093***	0.026	0.092***	0.031	-0.046	-0.020	-0.044	-0.014
	(0.022)	(0.024)	(0.022)	(0.025)	(0.038)	(0.031)	(0.036)	(0.030)
Area type	0.021	0.049*	0.016	0.037	0.008	-0.034	-0.008	-0.032
	(0.028)	(0.028)	(0.028)	(0.028)	(0.055)	(0.033)	(0.051)	(0.033)
Household income	0.000***	0.000***	0.000***	0.000***	-0.000**	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).

Child Outcomes

	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male
	Number of education years	Number of education years	Number of school days missed	Number of school days missed	School day missed dummy	School day missed dummy
MEPI	-0.755	-0.144	3.246*	1.645	0.417**	-0.167
	(0.560)	(0.490)	(1.660)	(1.959)	(0.200)	(0.177)
Dependent Dummy	0.154	-0.045	-1.862	-0.995	-0.260***	-0.210***
	(0.096)	(0.102)	(2.339)	(0.991)	(0.039)	(0.036)
Household size	-0.031*	-0.006	-0.022	0.001	0.003	-0.006
	(0.017)	(0.015)	(0.037)	(0.057)	(0.006)	(0.006)
Access to piped water	0.007	-0.024	0.093	0.007	0.006	-0.008
	(0.080)	(0.076)	(0.165)	(0.242)	(0.028)	(0.029)
Area type	-0.530**	-0.435	0.858	0.261	-0.065	-0.043
	(0.211)	(0.598)	(0755)	(0.492)	(0.078)	(0.117)
Household income	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mother employment (dummy)	0.007	-0.010	0.196	0.076	0.030	-0.001

	(0.061)	(0.075)	(0.169)	(0.169)	(0.025)	(0.026)
Mother education (years)	-	-	-	-	-	-
Access to sanitation	-0.221**	0.068	1.314**	-1.184***	0.014	-0.128***
	(0.105)	(0.157)	(0.594)	(0.449)	(0.039)	(0.045)

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).

O. Sensitivity Analysis – TPT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Satisfied	**Depressed**	**Overweight**	**Health Index**	**LF (strict)**	**LF (broad)**	**Stunting**	**Education years**	**Number of school days missed**	**School missed dummy**
TPT	-0.233***	0.126**	-0.043	-0.739***	-0.317***	-0.313***	0.061	-0.144	1.378*	-0.076
	(0.062)	(0.053)	(0.040)	(0.206)	(0.051)	(0.051)	(0.068)	(0.252)	(0.744)	(0.097)
Married	0.027	-0.016	0.043***	0.062	-0.013	-0.017	-	-	-	-
	(0.016)	(0.014)	(0.013)	(0.063)	(0.013)	(0.013)	-	-	-	-
Not Economically Active	-0.030***	0.022***	-0.009	-0.125***	-	-	-	-	-	-
	(0.010)	(0.009)	(0.007)	(0.034)	-	-	-	-	-	-
Dependent dummy	0.018	-0.012	0.004	-0.032	-0.014	-0.021*	-0.028	0.093	-0.007	-0.239***
	(0.013)	(0.012)	(0.008)	(0.047)	(0.012)	(0.012)	(0.020)	(0.069)	(1.057)	(0.026)
Education years	0.003	0.006	-0.000	-0.011	0.027***	0.037***	-	-	-	-
	(0.005)	(0.004)	(0.003)	(0.017)	(0.004)	(0.004)	-	-	-	-
Smoke Dummy	-0.002	0.003	-0.055***	0.235***	0.081***	0.076***	-	-	-	-
	(0.019)	(0.017)	(0.013)	(0.067)	(0.015)	(0.015)	-	-	-	-
Household size	-0.004*	0.002	-0.000	-0.010	-0.013***	-0.011***	0.006*	-0.021*	0.026	-0.003
	(0.002)	(0.002)	(0.001)	(0.007)	(0.002)	(0.002)	(0.003)	(0.011)	(0.037)	(0.004)
Piped water	0.024**	-0.010	-0.000	0.081**	0.035***	0.032***	0.013	-0.013	0.003	-0.001
	(0.011)	(0.009)	(0.007)	(0.037)	(0.009)	(0.009)	(0.014)	(0.053)	(0.137)	(0.020)
Dwelling type	-0.047**	-0.026	-0.023**	0.033	0.050***	0.046***	-	-	-	-
	(0.019)	(0.017)	(0.011)	(0.067)	(0.015)	(0.015)	-	-	-	-
Area Dummy	-0.013	0.046**	0.014	-0.059	0.045**	0.042**	0.031	-0.405*	0.391	-0.083
	(0.024)	(0.021)	(0.020)	(0.075)	(0.018)	(0.018)	(0.033)	(0.241)	(0.562)	(0.062)
Household income	0.000	-0.000	0.000**	0.000**	0.000***	0.000***	0.000	-0.000	-0.000	-0.000

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mother employment dummy	-	-	-	-	-	-	0.006	0.011	0.221*	0.015
	-	-	-	-	-	-	(0.014)	(0.048)	(0.132)	(0.019)
Access to sanitation	-	-	-	-	-	-	0.029	-0.124	0.273	-0.069**
	-	-	-	-	-	-	(0.024)	(0.086)	(0.347)	(0.028)

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model. Mother education (years) was included in the regression specification but due to the lack of variation, it was omitted.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).

P. Sensitivity Analysis – MEPI Definitions

	Life Satisfaction	Depressed	Overweight	Health Index	LF (strict)	LF (broad)	Unemployed (strict)	Unemployed (broad)	Stunted	Education Years	School days missed (number)	School days missed (dummy)
MEPI (Mendoza et al., 2019)	-0.154** (0.075)	-0.187*** (0.065)	0.109** (0.054)	0.175 (0.261)	-0.212*** (0.070)	-0.261*** (0.070)	0.584*** (0.116)	0.579*** (0.114)	-0.138 (0.099)	-0.696* (0.387)	2.008* (1.203)	-0.020 (0.133)
MEPI (Israel-Akinbo et al., 2018)	-0.154** (0.075)	-0.187*** (0.065)	0.109** (0.054)	0.175 (0.261)	-0.212*** (0.070)	-0.261*** (0.070)	0.584*** (0.116)	0.579*** (0.114)	-0.138 (0.099)	-0.696* (0.387)	2.008* (1.203)	-0.020 (0.133)
MEPI (Cut-off: 0.2)	-0.431*** (0.133)	-0.089 (0.112)	0.089 (0.089)	-0.529 (0.451)	-0.623*** (0.132)	-0.675*** (0.137)	1.641*** (0.344)	1.873*** (0.415)	-0.127 (0.139)	-0.987* (0.572)	2.693* (1.441)	-0.062 (0.191)
MEPI (Cut-off: 0.5)	-0.102* (0.053)	-0.139*** (0.046)	0.081** (0.038)	-0.529 (0.451)	-0.146*** (0.048)	-0.180*** (0.048)	0.370*** (0.086)	0.363*** (0.082)	-0.075 (0/073)	-0.557* (0.300)	1.815* (1.078)	-0.023 (0.106)
Observations	46,835	46,835	44,738	46,835	44,126	44,126	20,712	22,225	10,503	12,484	7,362	12,609
Number of pid	11,327	11,327	11,221	11,327	11,327	10,998	10,998	6,275	6,610	3,030	3,702	2,720

*Notes: Standard errors reported in parenthesis. Standard errors are robust, and the survey design is taken into account. Panel weights are applied. *p<0.05; **p<0.01; ***p<0.001. Province dummies and wave (time) dummies were included in the regression model.*

Source: NIDS wave 1 – wave 5 panel dataset (2008; 2010; 2012; 2014; 2017).