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Energy Transition and Household Well-being: Fuel Stacking, Power Reliability, and Solar Adoption Dynamics

By

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Declaration

I, Nouran Zenelabden, declare that this thesis is my original work. Any contributions from others have been appropriately acknowledged. I also declare that this thesis has not been submitted to support an application for any other degree or academic qualification at the University of Witwatersrand or any other higher education institution.

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Executive summary

This thesis explores the dynamics of home energy transition in South Africa, emphasizing three interconnected aspects: fuel stacking practices, their influence on power reliability, and patterns of solar adoption. Through a comprehensive empirical analysis of nationally representative data, this study provides valuable insights for promoting equitable access to clean energy and improving household well-being.

Preliminary analysis reveals unexpected correlations between fuel selection and health outcomes. Contrary to common beliefs, households employing fuel stacking (using clean and unclean fuels) experience worse health outcomes than those relying solely on clean or unclean fuel. This discovery underscores the significance of housing quality in mitigating health impacts, as inadequate ventilation and substandard construction materials exacerbate the detrimental consequences of mixed fuel use. This thesis highlights that older people and women are particularly susceptible to these adverse health effects, emphasizing the necessity for focused interventions.

Chapter two measures the impact of power outages on subjective well-being, revealing that frequent interruptions reduce self-reported happiness by approximately 10%. The effect varies significantly by region: urban areas show a 4.6% decrease, whereas nonmetropolitan areas exhibit a 2.9% reduction. The principal mechanism affecting this association is the disturbance of vital daily routines, including cooking habits and meal intake patterns. These findings underscore the need for reliable electricity access to sustain the quality of life.

Chapter three investigates household adoption of solar photovoltaic systems, noting that prolonged power disruptions elevate the likelihood of solar adoption by 1.9%. Female-headed households exhibit a greater tendency to adopt solar energy, indicating gender disparities in energy decision-making. Nevertheless, the study reveals that approximately one-third of solar users ultimately switch to non-renewable energy sources, primarily owing to financial constraints. This pattern underscores the need for continued economic assistance to facilitate the transition to renewable energy.

These significant implications for policy development support the implementation of comprehensive strategies that simultaneously address housing quality and energy accessibility, provide targeted assistance to vulnerable groups, and offer financial incentives for renewable

energy adoption. This study emphasizes the importance of gender-sensitive energy planning and the necessity to consider regional disparities in policy implementation.

This thesis enhances the literature on energy transition by providing substantial empirical information about the socioeconomic and behavioral dimensions of household energy decisions. It analyzes the intricate relationships among fuel selection, power reliability, and renewable energy adoption. In addition, this thesis provides practical recommendations for policymakers to enhance sustainable and equitable energy access in emerging regions. The findings provide a basis for subsequent investigations into energy justice and household welfare in the Global South.

Acronyms

2SLS: Two-stage least squares

ARIs: Acute respiratory infections

ATE: Average treatment effect

DML: Double machine learning

FBE: Free Basic Electricity

REIPPPP: Renewable Energy Independent Power Producer Procurement Program

IRP: Integrated Resources Plan

FE: Fixed effect regression

GHS: General household survey

IAP: Indoor air pollution

IPWRA: Inverse probability weighting regression adjustment

MDFE: Multidimensional fixed effects

ML: Machine learning

NN: Nearest neighbor matching

PM: Particulate matter

PSM: Propensity score matching

PSU: Primary sampling unit

PV: Solar photovoltaic

QoL: Quality of life

RE: Random effects regression

SWB: Subjective well-being

WHO: World Health Organization

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Chapter One: Introduction

1.1 Context and Rationale

South Africa presents a unique example of the challenges in energy transition, characterized by the paradox of high electrification rates alongside persistent energy poverty. Although over 90% of households are connected to the grid, the energy sector faces significant reliability and sustainability issues. The national energy infrastructure relies heavily on coal, producing more than 85% of electricity through the state-owned utility Eskom. This reliance ranks South Africa among the world's top 14 greenhouse gas emitters (IEA, 2023), causing local environmental and health concerns.

The current energy landscape illustrates South Africa's complex historical legacy and persistent energy injustices. During apartheid, the development of energy infrastructure mostly catered to industrial requirements and white communities, resulting in significant neglect of several regions, particularly rural "homelands" inhabited primarily by Black South Africans. This historical pattern established deep-rooted distributive injustices in energy access, where quality infrastructure and reliable services were concentrated in affluent areas. At the same time, marginalized communities were systematically excluded from energy development decisions—a clear violation of procedural justice principles.

After 1994, the democratic government emphasized expanding energy access through ambitious electrification initiatives, increasing coverage from 36% to more than 88% by 2022 (StatSA, 2022). However, this fast expansion created new obstacles, as infrastructure construction lagged behind the increasing demand. More critically, the focus on grid extension often failed to address the recognition justice dimensions of energy access, overlooking the distinct cultural practices, economic constraints, and social vulnerabilities of historically marginalized communities.

The nation is currently confronting multiple interrelated energy challenges. Since 2007, South Africa has experienced intermittent power outages because of inadequate generation capacity and deteriorating infrastructure. These outages significantly impede everyday life and economic operations, particularly affecting rural and low-income areas (Cole et al., 2018;

Klinger et al., 2014), highlighting persistent distributive injustices where vulnerable populations bear disproportionate burdens of energy system failures

Despite higher electrification rates, numerous households experience difficulties with energy costs, raising critical affordability justice concerns. Increasing electricity costs have surpassed income growth, compelling several households to adopt fuel stacking—using multiple energy sources, including traditional fuels, to satisfy their fundamental requirements. This adaptive strategy, while demonstrating household resilience, often exposes families to health risks and perpetuates energy poverty cycles.

Furthermore, the centralized energy system raises questions of responsibility and justice, as communities most affected by coal-fired power generation—particularly those in mining districts and impoverished areas—have had minimal voice in energy planning decisions while bearing the most significant environmental and health costs. The substantial dependence on coal poses considerable health and environmental issues, particularly in mining districts and impoverished communities where inadequate living conditions intensify indoor air pollution (IAP) from various fuel sources (Bohlmann & Inglesi-Lotz, 2018).

Infrastructure limitations worsen these challenges. Outdated power facilities, postponed maintenance, and inadequate investments in transmission infrastructure have resulted in a fragile supply situation. Eskom, the national utility, faces significant operational and financial difficulties, which impede efforts to improve reliability and ensure equitable service delivery. The government has enacted several policies to address these concerns. The Free Basic Electricity (FBE) program provides 50 kWh of complimentary electricity each month to eligible low-income households**,** representing an attempt to address affordability justice and facilitate the transition to cleaner fuels. The Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) promotes private sector participation in renewable energy generation; however, its development has been slower than anticipated, and questions remain about whether it adequately addresses procedural justice through meaningful community participation.

The Integrated Resource Plan (IRP) outlines the nation's long-term strategy for developing power infrastructure, including initiatives to diversify the energy mix by increasing renewable energy capacity. However, the extent to which this planning process incorporates recognition justice by acknowledging and addressing the diverse needs of different communities remains a subject of debate.

These policies function within a multifaceted institutional framework in which the national government sets overarching energy policies and regulations, Eskom oversees generation and transmission infrastructure, and municipalities control local distribution and implement social programs. The business sector has been progressively engaged in renewable energy development. Nonetheless, policy implementation encounters numerous obstacles, such as inadequate coordination across various governmental tiers, financial constraints on program viability, deficiencies in technical capability, and regulatory barriers to renewable energy adoption—all of which can perpetuate existing energy injustices.

These structural issues manifest intricately at the domestic level. Impoverished households frequently utilize various fuel sources, weighing cost factors against availability and dependability. Although fuel stacking enhances resistance to supply interruptions, it may pose significant health risks, particularly in regions with little house ventilation. Energy poverty disproportionately impacts women and children, who are more frequently affected by IAP and are primarily responsible for fuel collection and management (Ali et al., 2021; Nkosi et al., 2021), highlighting how energy injustices intersect with gender and age-based vulnerabilities. This complex context, viewed through the lens of energy justice, illustrates the interconnected topics addressed in the following chapters of this thesis. Chapter Two examines the correlation between fuel stacking practices and health outcomes, emphasizing the moderating role of house quality in these impacts—directly addressing recognition justice by acknowledging how housing quality shapes energy-health relationships. Chapter Three analyzes the effects of power outages on subjective well-being (SWB), measuring the societal costs associated with unstable electricity supply and revealing distributive injustices in how energy system failures impact different communities. Chapter Four examines families' adoption of solar photovoltaic (PV) systems, investigating the factors promoting and hindering the transition to renewable energy while exploring procedural justice in household energy decision-making and affordability justice in technology access.

1.2 Research Objectives

This dissertation examines three key aspects of South Africa's energy transition through the comprehensive framework of energy justice. The primary goal is to understand how various dimensions of energy justice are reflected in household energy experiences and to identify pathways toward more equitable energy transitions.

The primary objective of this thesis is to examine the multifaceted nature of energy justice in South Africa's energy transition by analyzing the interplay between fuel stacking practices, power system reliability, and renewable energy adoption at the household level.

Specific Objectives:

1. **Distributive and Recognition Justice in Energy-Health Relationships**: Analyze the relationships between fuel stacking and health outcomes, focusing on the moderating role of home quality in these impacts. This objective addresses how energy burdens and benefits are distributed across different housing types and communities, using double machine learning (DML) methodologies to assess the health effects of various fuel consumption patterns while recognizing the distinct vulnerabilities of different household types.

2. **Distributive and Responsibility Justice in Energy Reliability**: Quantify the impact of power interruptions on subjective well-being (SWB) using self-reported happiness measures. This objective quantifies how the costs of energy system failures are distributed across different communities and examines questions of responsibility for maintaining reliable energy services. Panel data analysis is employed to measure the societal costs associated with inconsistent energy supply across various locations.

3. **Procedural and Affordability Justice in Energy Transitions**: Investigate the determinants of household adoption of photovoltaic (PV) systems, exploring the factors facilitating and hindering the transition to renewable energy with particular attention to gender dynamics in decision-making. This objective examines how procedural aspects of energy decision-making within households intersect with affordability constraints and access to renewable energy technologies.

These objectives are addressed through three empirical studies that collectively provide comprehensive evidence on energy justice dimensions in South Africa's energy transition.

1.3 Theoretical Framework

This thesis is grounded in a comprehensive energy justice framework that offers a multidimensional perspective for understanding energy transitions in developing contexts.

Energy justice highlights the importance of equitable access to clean, affordable, and sustainable energy, while acknowledging the complex social, economic, and political factors involved in energy systems.

1.3.1 The Complete Energy Justice Framework

This thesis is rooted in the multifaceted concept of energy justice, a crucial framework for understanding and addressing the inherent inequities within energy systems (Jenkins et al., 2020). At its core, energy justice seeks to ensure that the benefits and burdens associated with energy production and consumption are distributed equitably across all segments of society (Sovacool et al., 2017). This framework is particularly vital in contexts marked by historical and ongoing disparities, such as South Africa, where the enduring legacy of apartheid continues to profoundly shape access to resources and opportunities (Volodzkienė & Štreimikienė, 2023). The dimensions of energy justice, as outlined by Sovacool et al. (2023), provide a comprehensive lens through which to analyze and rectify these imbalances within the South African energy landscape.

The theoretical foundation of this thesis rests on five interconnected dimensions of energy justice, each profoundly relevant to the South African context. Distributive Justice directly concerns the equitable distribution of energy resources, infrastructure, benefits, and burdens across different communities, regions, and social groups. In South Africa, this involves examining how disparities in energy access, quality, and reliability persist across racial, economic, and geographic lines, and how the negative externalities of energy production, such as pollution and health impacts, disproportionately affect marginalized communities.

Procedural Justice emphasizes inclusive, transparent, and participatory decision-making processes in energy policy, planning, and implementation. For South Africa, this dimension questions whether historically disadvantaged communities have meaningful opportunities to participate in the energy decisions that directly affect their lives, from national policy formulation to local energy project choices. Recognition Justice acknowledges the distinct needs, capabilities, cultural practices, and vulnerabilities of different communities, particularly those historically marginalized. This is crucial in South Africa, where factors such as gender, race, class, and geographic location (e.g., urban vs. rural, informal settlements) profoundly shape diverse energy experiences and needs.

Affordability Justice focuses on ensuring that energy services are financially accessible to all households, regardless of income level. In the South African context, this dimension examines not only the direct costs of energy but also the broader economic impacts of energy poverty and the effectiveness of policies designed to ensure genuinely affordable access for all.

Finally, Responsibility Justice addresses the critical question of who bears responsibility for energy system failures, environmental costs, and the provision of universal energy access. This involves scrutinizing the roles and accountability of various actors, including government bodies, state-owned utilities, private companies, and communities themselves, in ensuring just energy transitions in South Africa. Together, these five dimensions form a robust analytical framework for dissecting and proposing solutions to South Africa's complex energy challenges.

1.3.2 Integration with Energy Consumption Frameworks

This comprehensive energy justice framework is integrated with established theories of household energy consumption behavior. The energy ladder model suggests that households progress from traditional fuels to modern energy sources as income increases, In contrast, the fuel stacking framework recognizes that households often use multiple energy sources simultaneously based on availability, affordability, and reliability considerations.

These consumption frameworks are reinterpreted through the energy justice lens to understand how households navigate energy choices within contexts of systemic inequality and injustice. Fuel stacking, for instance, can be understood not merely as a transitional behavior but as an adaptive strategy employed by households facing multiple energy injustices—where unreliable grid electricity, unaffordable tariffs, and inadequate infrastructure compel diversified energy portfolios.

1.3.3 Theoretical Linkages Across Chapters

The energy justice framework provides theoretical coherence across the three empirical chapters:

- **Chapter 2** employs distributive and recognition justice lenses to examine how fuel stacking practices and their health impacts vary across different housing types and communities, recognizing that energy-health relationships are shaped by structural inequalities.

- **Chapter 3** applies distributive and responsibility justice perspectives to analyze how power outages affect subjective well-being differently across communities, revealing who bears the costs of energy system failures and raising questions about responsibility for reliable service provision.

- **Chapter 4** utilizes procedural and affordability justice frameworks to examine household solar PV adoption, exploring how decision-making processes within households intersect with financial constraints and access to emerging energy technologies.

1.4 Conceptual Framework and Chapter Linkages

The conceptual framework below illustrates how the five dimensions of energy justice interact with South Africa's energy transition challenges to shape household energy experiences.

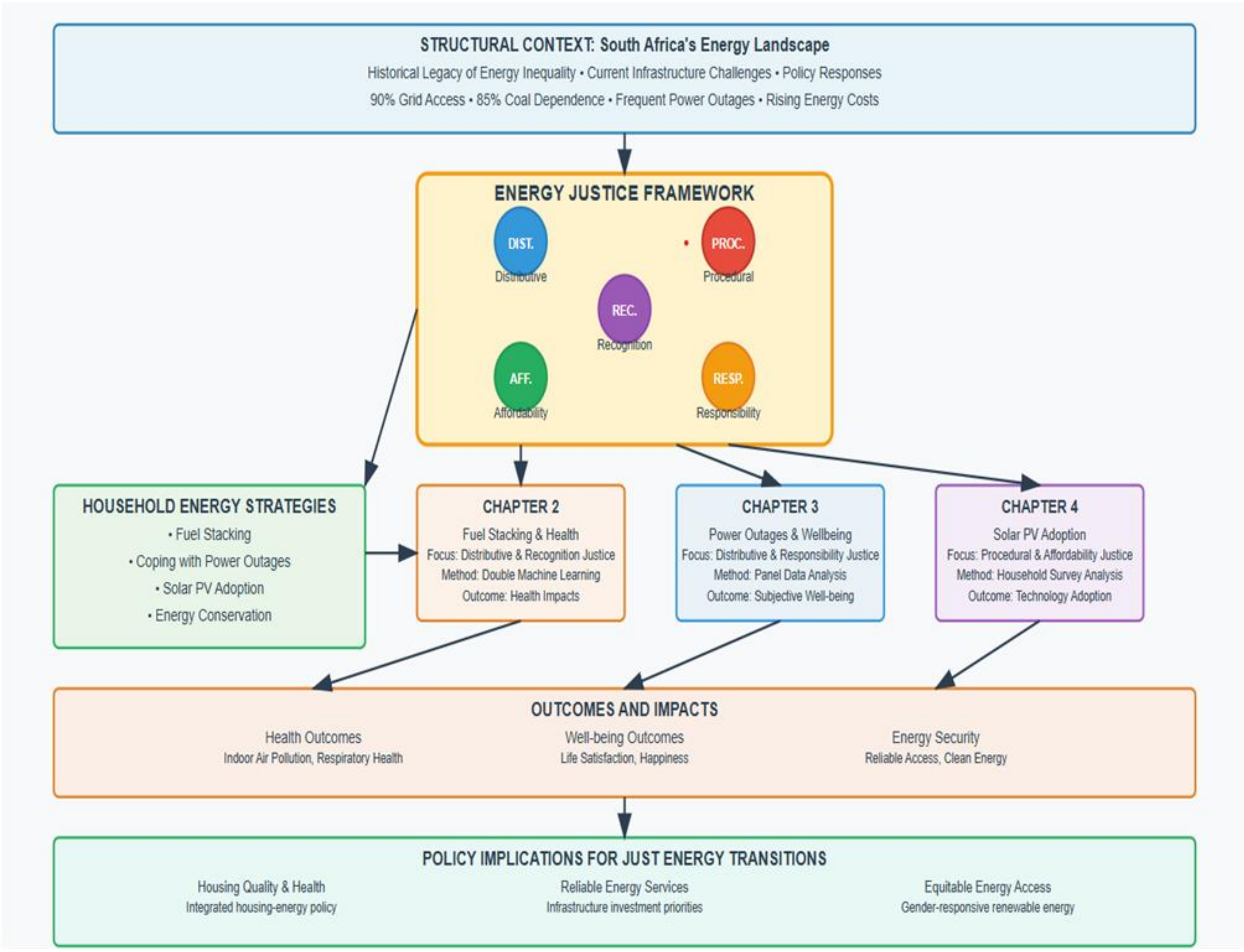

Figure 1.1: Conceptual Framework -Energy Justice Dimensions and Chapter linkages

The framework demonstrates the theoretical and empirical linkages between the three core chapters of this dissertation:

Structural Context: South Africa's historical legacy of energy inequality, current infrastructure challenges, and policy responses create the structural context within which households navigate energy decisions.

Energy Justice Dimensions: The five dimensions of energy justice (distributive, procedural, recognition, affordability, responsibility) provide analytical lenses for understanding how structural inequalities manifest in household energy experiences.

Household Energy Strategies: Within this context of energy injustice, households employ various adaptive strategies, including fuel stacking, coping with power outages, and adopting new technologies like solar PV systems.

Outcomes and Impacts: These strategies produce differentiated outcomes across health, well-being, and energy security dimensions, which are analyzed in the three empirical chapters.

Policy Implications: The findings from each chapter inform policy recommendations for addressing different dimensions of energy justice and promoting more equitable energy transitions.

1.5 Significance of the Study

This study advances both academic understanding and policy development in multiple interconnected ways, with particular emphasis on its contributions to energy justice scholarship and practice.

1.5.1 Theoretical Contributions

Energy Justice Framework Development: This thesis contributes to the growing body of energy justice literature by providing one of the first comprehensive applications of the complete five-dimensional energy justice framework to analyze household energy experiences in a developing country context. The integration of energy justice theory with established energy consumption frameworks offers a more nuanced understanding of how households navigate energy choices within contexts of systemic inequality.

Methodological Innovation: The study advances the application of sophisticated econometric techniques in energy transition research by utilizing double machine learning (DML) methods and robust panel data analysis within an energy justice framework. This methodological approach offers more rigorous causal identification while remaining attentive to issues of equity and justice.

Intersectional Analysis: By examining how energy justice dimensions intersect with gender, race, class, and geographic location, this study contributes to understanding the complex, intersectional nature of energy inequality and its implications for just energy transitions.

1.5.2 Policy and Practice Implications

Comprehensive Policy Framework: The findings provide practical guidance for policymakers aiming to enhance equitable energy access by addressing all dimensions of energy justice simultaneously rather than focusing on single aspects like grid extension or renewable energy deployment.

Evidence-Based Interventions: By analyzing the relationships among energy consumption patterns, health outcomes, and well-being through an energy justice lens, this study identifies more effective intervention strategies for alleviating energy poverty while promoting health and well-being.

1.5.3 International Relevance

Global South Applications: South Africa's experience provides significant insights for other developing nations undergoing comparable energy transitions, particularly those grappling with similar legacies of inequality and resource extraction.

Sustainable Development Goals: The findings contribute to international efforts to achieve Sustainable Development Goal 7 (affordable and clean energy) by demonstrating how energy justice considerations can inform more effective and equitable energy transition strategies.

Climate Justice: As countries worldwide grapple with the challenge of transitioning away from fossil fuels while ensuring equitable access to clean energy, this study provides evidence on how to navigate these tensions through comprehensive attention to energy justice.

1.5.4 Contribution to Energy Transition Scholars

This dissertation contributes to the emerging field of just energy transitions by demonstrating how attention to energy justice can inform more effective and equitable energy policies. The integrated analysis of fuel stacking, power reliability, and renewable energy adoption provides a comprehensive view of how households experience energy transitions and how policy interventions can better support equitable outcomes.

The study's emphasis on the complete energy justice framework offers a more holistic approach to understanding energy transitions than previous research that has focused on single dimensions of energy access or individual technologies. By examining the interconnections between distributive, procedural, recognition, affordability, and responsibility justice, this research provides a roadmap for more comprehensive and effective energy transition policies.

1.6 Structure of the Dissertation

The remaining chapters are structured as follows. Chapter Two investigates fuel stacking and health outcomes using DML to assess how housing factors influence the health effects of various fuel combinations. Chapter Three examines the correlation between power outages and SWB, employing panel data analysis to measure impacts across geographic and demographic contexts. Chapter Four analyzes solar adoption trends, investigates obstacles to and facilitators of renewable energy transition, and discusses gender dynamics in family decision-making. Chapter Five consolidates findings from chapters 2-4, examines policy implications, and proposes avenues for future research.

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Chapter Two: Fuel Stacking, Housing Quality, and Health Disparities in Rural South Africa: A Double Machine Learning Approach

Abstract

This chapter examines the complex relationships between household fuel choices, housing conditions, and health outcomes in rural South Africa, focusing on the practice of "fuel stacking." We employ a DML approach to estimate the health impacts of different fuel use patterns using data from the 2019 Statistics South Africa General Household Survey (Stats SA GHS). Our analysis distinguishes between clean, unclean, and mixed fuels to capture the nuanced effects of fuel stacking behavior. The findings reveal that fuel stacking (using mixed fuels) is associated with poorer health outcomes compared with the exclusive use of clean fuels, with the greatest impact observed among older people. Surprisingly, mixed fuel use is also linked to worse health outcomes than relying solely on unclean fuels, challenging the assumption that partial transitions to cleaner fuels yield health benefits. Although no significant gender disparities were observed in the health effects of mixed fuel use, the negative impact of unclean fuels (compared to clean fuels) was significant only for females. Furthermore, this study uncovers a strong association between fuel stacking and poor housing conditions, highlighting the intricate interplay between socioeconomic factors, fuel choices, and health. These findings underscore the need for comprehensive policies addressing fuel type, housing quality, and socioeconomic vulnerability to ensure an equitable and effective clean energy transition in rural South Africa.

Keywords: Fuel stacking; Double machine learning; Indoor air pollution; Housing quality; Health disparities; Rural energy transition

JEL Codes: Q42, I15, R20, C55

2.1 Introduction

Indoor air pollution (IAP) is a critical global environmental and public health challenge, disproportionately affecting the world's most economically vulnerable populations. The World Health Organization (WHO, 2022) estimates that approximately 2.4 billion people will rely on polluting fuels for cooking and heating in 2020, with 2.1 billion people expected to continue this practice in 2030, predominantly in low- and middle-income countries. This issue is exacerbated by significant disparities between urban and rural areas, with 52% of the global rural population dependent on polluting fuels compared to 14% of the urban population (Mohajeri et al., 2023; WHO, 2024).

The situation in South Africa is particularly acute. Pauw (2017) reported that approximately 30% of the population use unclean fuels, whereas approximately 50% use fuel stacking practices. This prevalence is attributed to a complex interplay of factors, including high electricity costs, inadequate infrastructure, and geographic disparities. The use of traditional unvented stoves and open fireplaces, especially in rural areas, results in elevated IAP levels, emitting health-damaging pollutants that can lead to acute and chronic health conditions (WHO, 2024; Gordon et al., 2014).

The health impacts of IAP are not uniformly distributed across populations. Women and children in low-income rural households face prolonged exposure to high IAP levels, significantly increasing their risk of acute respiratory infections (ARIs) and other health issues (StatSA, 2016; WHO, 2011, 2012). Recent studies have highlighted the vulnerability of older people to IAP (Wu, 2022; Liu et al., 2018). Pauw (2017) declared that IAP affects 20% of rural households in South Africa and is responsible for approximately 1,400 child deaths annually. Globally, WHO (2019) attributed 4 million premature deaths annually to IAP, with lung cancer, cardiovascular diseases, ARIs, and pneumonia being the primary causes.

Although extensive studies have been conducted on the health effects of unclean fuel use, geographic bias has been observed in the literature, as most studies were conducted in China (Liu et al., 2020; Tian et al., 2021). Accordingly, a significant gap exists in understanding the fuel–health nexus in sub-Saharan Africa, particularly in South Africa. Region-specific research is highly required to inform targeted policy interventions and achieve sustainable development and climate change goals.

A critical review of the literature reveals methodological limitations. Previous studies have predominantly employed binary treatment approaches, focusing on cooking fuel choices (Liu et al., 2020; Tatham and Muchapondowa, 2021; Twumasi et al., 2021). This binary approach fails to capture the nuanced reality of fuel use patterns, particularly fuel stacking. The heterogeneity of exposure resulting from multiple fuel use likely has significant implications for health outcomes. In addition, the binary treatment approach may lead to over- or under-estimation of the proper relationship between fuel choices and health. Only Hou et al. (2022) investigated fuel stacking behavior in relation to self-reported general health status. However, limitations such as a small sample size and geographic specificity restrict the generalizability of the findings.

This study aims to address these gaps and contribute to current literature. First, a more nuanced approach to the classification of fuel choice was employed, constructing a fuel index that included clean, mixed, and unclean fuels. This approach captures the complexities of fuel choices for cooking and heating in rural South Africa and provides a more accurate representation of energy transition patterns and their health implications. Second, this study uses rich, nationally representative data from Stats SA GHS (2019), focusing on rural households. Accordingly, health outcomes across different subgroups were analyzed in detail, contributing to a more inclusive understanding of the fuel–health nexus.

Third, we incorporate housing characteristics by including variables related to housing structure and construction materials. Accordingly, this study addresses a significant oversight in previous economic literature and provides a more holistic understanding of the factors influencing fuel choices and their health effects. Finally, DML, as proposed by Knaus (2021), was employed to address the methodological challenges in estimating the relationship between fuel choices and health outcomes. In addition, two-stage least squares (2SLS) regression was applied to check the robustness of the results to unobserved factors, addressing potential endogeneity issues. This approach represents a novel contribution.

The significance of this study goes beyond academic contributions. By thoroughly examining the relationship between fuel choices and health outcomes in rural South Africa, this research can inform and influence energy policies, encourage the shift to cleaner energy sources, and aid in tracking progress toward sustainable development and climate change objectives.

The following sections present a detailed background on the issue. Subsequently, we provide a comprehensive literature review that outlines the theoretical framework, determinants of fuel choices, and established relationships between IAP from fuel choices and health outcomes. The methodology, data sources, and descriptive statistics are also presented. The results section offers a detailed analysis of the findings and a discussion contextualizing these results within the broader literature and policy landscape. In conclusion, this study provides policy recommendations and suggestions for future research directions.

2.2 Background

South Africa is one of the most unequal countries in the World Bank's global poverty database, as indicated by its Gini coefficient, which places it among the highest-ranked of 164 nations (Sulla et al., 2022; World Bank, 2020). This inequality is attributed to the legacy of apartheid, a system of racial segregation and discrimination that excluded "people of color" from access to state resources and denied them fundamental human rights.

After the end of apartheid in 1994, the new government in South Africa introduced policies to address persistent inequalities. A key focus was improving access to essential services, including free electricity for low-income households (Stats SA, 2019). Initiatives such as the National Electrification Programme (1994–2001) and its successor, the Integrated National Electrification Programme, prioritized electrifying rural areas. In addition, the IRP, launched in 2010, emphasized the development of renewable energy, mainly for communities that do not have access to the national grid (Rathi and Vermaak, 2018). Despite some implementation problems, electrification programs have effectively increased overall electricity accessibility, although rural areas tend to lag.

South Africa exhibits diverse and complex patterns of household fuel use shaped by location, cultural norms, income, and fuel availability. In rural areas with scarce or expensive electricity, readily available wood often serves as the primary source of fuel. In addition, low-income urban households frequently rely on kerosene. Households near coal mines in Mpumalanga Province usually use coal for cooking and heating. This variation in fuel choices highlights the diverse socioeconomic and environmental conditions across different regions in South Africa (Roomaney et al., 2022).

Although South Africa boasts a high electrification rate, with 89% of households connected to the grid as of 2021, electricity is not the primary cooking fuel for all. Financial constraints hinder low-income households from relying solely on electricity, even with reduced tariffs and a monthly free basic allowance (50–60 kWh) for essential needs like lighting and phone charging. Stats SA (2021) reported that although electricity dominates as a cooking fuel (77.7%), a significant portion of households depend on wood (7.7%), kerosene (3.5%), and coal (0.4%). These percentages indicate ongoing challenges in achieving universal access to clean fuels in South Africa despite advancements in electrification.

The IAP issue in South Africa presents a complex public health challenge. Studies on air quality in South Africa have reported that low-income communities face the highest levels of ambient particulate matter (PM), surpassing concentrations in industrial regions (Adesina et al., 2020; Piketh et al., 2016). According to Roomaney et al. (2022), 17.6% of South Africans were exposed to IAP in 2012, leading to an estimated 8,862 deaths that year, primarily caused by respiratory infections and cardiovascular diseases. IAP exposure resulting from the burning of unclean fuels varied by province, with the most significant percentages in 2012 in KwaZulu-Natal (26.4%), Mpumalanga (27.4%), and Limpopo (50.0%).

Consequently, an investigation of household energy choices and their impacts on health is crucial for designing effective policies that promote the transition to cleaner energy sources while addressing energy poverty and gender disparities.

2.3 Theoretical Frameworks and Determinants of Fuel Choices

2.3.1 Theoretical Review

Access to clean and affordable energy remains a significant challenge in developing countries, with profound implications for public health and socioeconomic development. Despite increased electrification efforts in South Africa and similar contexts, many households still rely on traditional biomass fuels for cooking and heating (Bohlmann and Inglesi-Lotz, 2018; SEA, 2016). This ongoing use of solid fuels contributes to IAP, which is linked to various adverse health outcomes, especially among vulnerable populations (Edwards, 2012; Wang et al., 2016).

Understanding the complex dynamics of household fuel choices and their health impacts is crucial for developing effective interventions and policies. This review critically evaluates the current state of knowledge in this area. Additionally, this study aims to identify key research gaps by synthesizing and critically analyzing the existing literature.

Two main theoretical frameworks have dominated the study of household fuel choices: the energy ladder and fuel stacking. Hosier and Dowd (1987) introduced the energy ladder model, which posits a linear progression from traditional biomass fuels to modern, cleaner energy sources as household income increases. However, this model has been criticized for oversimplifying the fuel transition process and neglecting non-economic factors (Van der Kroon et al., 2013).

In response to these limitations, Masera et al. (2000) proposed the fuel stacking model, which recognizes that households often adopt new cooking technologies while maintaining traditional methods. This model offers a more nuanced understanding of household energy use patterns by considering factors beyond income, such as cultural preferences and supply constraints (Batchelor and Brown, 2021).

Although the fuel stacking model represents an advancement in conceptualizing household energy transition, it has limitations. It requires greater quantitative predictive power and may need to better address supply-side factors and market dynamics (Ruiz-Mercado and Masera, 2015). Recent studies have further recommended a more comprehensive overarching theory that would integrate aspects of both these paradigms, considering perspectives from behavioral economics and sociotechnical transition theory (Kowsari and Zerriffi, 2011; Van der Kroon et al., 2013).

Another work that contributed to this conversation is Kowsari and Zerriffi (2011), specifically their concept of a "three-dimensional energy profile." This construct examines the physical properties of energy carriers and devices, the peculiarities of energy services, and the socioeconomic and cultural factors influencing fuel choice. This model can explain why some households may engage in unhealthy fuel-stacking practices despite clear adverse health effects. The authors assert that fuel selection is part of the overall household decision-making process related to living and housing conditions.

The theoretical connections between fuel use and health effects were found to have empirical corroboration. Ruiz-Mercado and Masera (2015) argued that health impacts associated with fuel selection are mediated by housing, behavioral, and technical factors, providing some insights to comprehend why mixed-fuel employments used turned out to have worse health impacts. This framework was upgraded by Checkley et al. (2016), who held that housing conditions formed "microenvironments" in which health impacts related to fuel selection might be amplified or muted. Poor housing conditions might also trigger "feedback loops" that heighten pollutant exposure related to insufficient ventilation, decrease combustion fuel efficiency related to excessive dampness, and absorption and re-emission of pollutants due to specific building materials.

2.3.2 Understanding Household Fuel Choice: Determinants and Transition Factors

3.2.1 Diverse Factors Influencing Fuel Selection

Empirical studies have identified various factors influencing household fuel choices, broadly categorized into economic, sociodemographic, and geographic/infrastructural determinants. Income and wealth consistently emerge as significant predictors of fuel choices, with higher-income households more likely to use cleaner fuels (Zhu et al., 2022; Wassie et al., 2021). However, the relationship between income and fuel choice is not always linear, and the income threshold for transitioning to cleaner fuels varies across contexts (Muller and Yan, 2018). Credit accessibility also enables rural households to switch to cleaner energy sources (Twamsi et al., 2020). However, studies on the long-term sustainability of credit-enabled fuel transitions have been insufficient.

Education levels are consistently associated with preferences for cleaner energy sources (Qiu et al., 2023; Dongzagla and Adams, 2022). However, the mechanisms through which education influences fuel choices beyond the associated income effects require further investigation. Gender dynamics are significant in energy poverty, particularly in rural regions (Liu et al., 2020; Hou et al., 2023). Women and girls often bear the burden of collecting and using traditional biomass fuels, highlighting the need for gender-sensitive energy policies and interventions.

3.2.2 Fuel Transition Intricacies

Fuel switch trends in developing contexts highlight a highly non-linear path. The fuel choices made by households are complex and involve adopting multiple types of fuel due to volatility in supply and economic prospects. The cultural and behavioral dimensions are also significant, as households often adhere to traditional fuel usage despite the availability of modern fuels (Ruiz-Mercado and Masera, 2015).

The second step involves establishing incentives for parents to overcome the switch barrier and adopt cleaner fuel technologies. Transition towards cleaner fuel technologies implies not only access to technologies but also overcoming ingrained habits. According to research by Carter et al. (2019), households would need to abandon old solid fuel technologies to adopt cleaner ones. Unless the new cleaner fuel options have more attractive prospects, the established sociotechnical systems would continue to prevail.

Demographic factors play an important role in fuel switching. Based on research conducted by Elasu et al. (2024), households headed by elderly individuals are more likely to use traditional fuels due to financial constraints and the high costs associated with switching from conventional to clean cooking fuels. According to Sharma (2019), even though households intend to switch to clean fuels such as LPG and electricity, they remain stuck at the bottom tier of the energy ladder due to economic reasons and values.

Another important determinant is the availability of infrastructure. As stated by Rosenthal et al. (2018), the overlap between old and new technologies is more frequently found in areas with high clean fuel prices and underdeveloped distribution systems; thus, the reason interventions neglecting the local infrastructure usually do not work.

"Fuel stacking" introduces more complexity in potential transition pathways. Malakar and Day (2020) argued that households with access to cooking with LPG still chose to rely on firewood as they believed that the food taste and the cooking steps associated with certain foods require the use of biomass fuels. This implies that specific households may never fully transition from traditional to modern fuels, and policies should be designed to accommodate this outcome instead of attempting to impose a one-dimensional transition pathway.

The study by Hanna et al. (2016) shows that the health benefits of new fuel alternatives can be negated by behaviors associated with them. This means that providing cleaner fuels alone does not necessarily lead to improvements in health, as the practice of using harmful fuels continues, often due to socio-cultural dynamics or a lack of alternatives.

Housing conditions play a crucial role in mediating the effect of fuel use on health. Structural housing characteristics, including ventilation systems, room configuration, and building design, are correlated with the emission of harmful pollutants produced when fuels are combusted. The influence of housing characteristics on fuel use also highlights the limitations of policies that promote fuel switching but employ a generalized approach to achieve expected health impacts (Bruce et al., 2015).

2.3.3 Health Impacts of Indoor Air Pollution from Fuel Use

Numerous studies have linked IAP from solid fuel use to various health problems, including respiratory infections, cardiovascular diseases, and adverse birth outcomes (Edwards, 2012; Wang et al., 2016). Health impacts appear particularly pronounced among vulnerable groups, such as children, women, and older people (Krishnamoorthy et al., 2022; Xu et al., 2022; Liang et al., 2020).

In the South African context, several studies have focused on the relationship between IAP and respiratory illnesses in children. Barnes et al. (2009) argued that IAP increases the risk of ARIs in young children because of their immature lungs and immune systems. Albers et al. (2015) reported a significantly higher rate of respiratory diseases among schoolchildren in Mpumalanga residing in households that used non-electric cooking fuels. Similar patterns have been observed in other regions of South Africa (Buthelezi et al., 2019; Shirinde et al., 2014).

Despite the substantial body of evidence linking solid fuel use to adverse health outcomes, various methodological challenges complicate the interpretation of these findings. Several studies have relied on proxy exposure measures (e.g., fuel type) rather than direct measurements of pollutant concentrations, potentially leading to exposure misclassification. Socioeconomic status, nutrition, and access to healthcare can confound the relationship between fuel use and health outcomes, complicating the isolation of the specific effects of IAP. Most studies have focused on short-term health impacts, neglecting the potential long-term consequences of chronic exposure to IAP.

These methodological limitations partly explain some of the conflicting evidence in the literature. Tatham and Muchapondwa (2021) reported a slight increase in ARIs and general respiratory illnesses associated with solid fuel use in rural South Africa. The effects were not statistically significant for specific age and gender subgroups. This finding contradicts other studies that revealed more pronounced health impacts, particularly among women and young children.

This critical review focuses on South Africa and highlights the complex interaction between household fuel choices and health impacts in developing countries. Although significant progress has been made in understanding the determinants of fuel choices and associated health risks, several important research gaps and methodological challenges still exist.

2.4 Methodology

Machine learning (ML) is gaining popularity in energy economics because of its superior performance in processing, categorizing, and predicting large-scale and complicated data (Ghoddusi et al., 2019). As ML models do not make any prespecified assumptions about the functional form of the equation, the interaction between variables, and the statistical distribution of parameters, they can manage large amounts of structured and unstructured data and make quick decisions or forecasts (Athey, 2017; Mullainathan and Spiess, 2017). Accordingly, the ML methods have an advantage over methods proposed by classical econometrics.

A recent development in the application of ML models is in causal inference, whereas traditional ML focuses on predicting outcomes. Causal ML, on the other hand, leverages this predictive power to quantify changes in outcomes due to treatment (Feuerriegel et al., 2024). Specifically, ML models can be applied in the context of the well-known Propensity Score Matching (PSM) to account for selection on observables. This offers an improvement on PSM because it can flexibly account for higher-order and interaction terms, leveraging the variable selection attributes of ML models. The implementation of causal machine learning used in our analysis is called Double Machine Learning (DML).

Doubly robust machine learning (DML) is a data-driven approach that improves the plausibility of the ignorability assumption[1] by offering more flexibility in defining the propensity score equation. This is achieved by controlling complex interactions and higher-order terms, which can increase the number of variables and potentially impact the common support assumption (Chernozhukov et al., 2018; Knaus, 2021; Bodory et al., 2022). However, mitigates this by relying on the spacing assumption, which improves the plausibility of the standard support assumption. In contrast to the single-equation approach that uses either the outcome or the propensity score model to estimate the treatment effect under the ignorability assumption (e.g., propensity score matching (PSM)), DML is considered “doubly robust”; it remains consistent even if the outcome or treatment equation is incorrectly specified (Knaus, 2021).

The DML approach of Knaus (2021) was applied in this analysis to investigate the health impacts of fuel choices in binary and multivalued treatment settings with different treatments from a random set random set $D_i \in$ {0, 1, ….T}, T=3 (i.e., treatment levels clean, mixed, and polluting fuels). Thus, we estimate the average potential outcomes (APO) $\mu_t = E[Y_i^t]$ and their differences. Following Knaus (2021), we estimate the average treatment effect (ATE) for the difference in possible outcomes $\mu_1 - \mu_0 = E[Y_i^1 - Y_i^0]$. We also consider various pairwise

[1] This entails the conditional independence and the common support assumption.

comparisons that could be made for the multivalued treatment, such as $\mu_m - \mu_k$ =E$\left[Y_i^m - Y_i^k\right]$ for m≠k D_i ∈ {0, 1, ….T}. The average potential outcomes conditional on covariates are obtained as follows:

$$\mu_t = E\left[\mu_t(X_i) + \frac{d_i^t\big(Y_i - \mu_t(X_i)\big)}{p_t(X_i)}\right], \qquad (2.1)$$

where $d_i^t = \{D_i = t\}$ is the treatment indicator, $\mu_t(x)$ represents the predictions for the conditional outcome, and $p_t(X_i)$ denotes the predictions for the propensity score:

$$\sigma_{\mu,t}^2 = E\left[\left(\frac{d_i^t\big(Y_i - \mu_t(X_i)\big)}{p_t(X_i)} + \mu_t(X_i) - \mu_t\right)^2\right], \qquad (2.2)$$

The post-model-selection problem does not affect the validity of the statistical inference on the possible outcome.[2] To implement the DML, we used LASSO as a variable selector to obtain the predictions for the outcome $\mu_t(x)$, and the propensity scores $p_t(x)$. Subsequently, these predictions are inserted into the sample analogs of equations (1) and (2) to estimate the average potential health outcomes (e.g., self-reported poor health and ARI). Differences among the three categories of fuel choices are estimated to obtain the multivalued treatment effect. The parameters $\mu_t(x)$ and $p_t(x)$ are estimated using post-LASSO with cross-validation. Post-LASSO is based on the LASSO estimator proposed by Tibshirani (1996). LASSO solves the following optimization problem:

$$\min_{\beta}\left[\sum_{i=1}^{n}(Y_i - X_i\beta)^2\right] + \lambda\sum_{j=1}^{p}|\beta_j|, \quad (2.3)$$

where Y_i is the observed outcome, X_i is a vector of covariates, and λ is a penalty factor on the total of the absolute coefficients. In the analysis, 17 variables and a model with second-order terms encompassing more than 137[3] covariates were controlled for. Therefore, coefficients may be too small to be of significance. In this case, LASSO acts as a variable selector. It reduces to

[2] In Knaus (2021), formulas are provided to derive the pairwise ATEs by deducting the doubly robust scores of possible outcomes.
[3] The analysis was conducted using **R** version 4.1.1 (2021-08-10) within **RStudio** (version 2022.07.0+548). We employed the dmlmt function from the relevant package to estimate a double machine learning model for a binary and multivalued outcomes. For further details on the implementation, relevant packages, and code structure, see Kanus (2021).

zero any variables with little or no predictive power (depending on the value of λ) selected by cross-validation

It is important to note that the primary objective of using the DML framework is to estimate the causal impact of fuel choices on health outcomes, not to investigate the independent effects of covariates such as age, income, or education on health. DML, like propensity score matching, relies on covariate balancing to isolate the treatment effect. Consequently, once covariates are balanced between treatment groups (e.g., clean vs. mixed fuel users), their variation is no longer available to explain health outcomes directly. Thus, while these covariates are essential for identifying the treatment effect, any post-matching correlation between them and the outcome should not be interpreted as causal. This trade-off is inherent in causal inference approaches that aim to eliminate confounding, and it aligns with the study's focus on fuel-use impacts.

To evaluate the robustness of our results to unobserved factors, we employed the 2SLS estimation approach to account for model uncertainty related to variable selection and endogeneity bias. We used the proportion of people at the primary sampling unit (PSU) level who used unclean fuels at home as an instrument (IV) for fuel choices because the acceptance of modern technology is frequently affected by other residents in the community (Conley and Udry, 2010). The fuel preferences of other households may have little to no effect on the indoor air quality of a particular household, but they should not impact the outcome variable (Liu et al., 2020). In the literature, using the average perception of other people as an instrumental variable is a reliable IV for determining fuel preferences (Liu et al., 2017; Liu et al., 2020). Lewbel's (2012) heteroscedastic-based technique was also used to create additional instrumental variables. This approach, along with the IVs, has been employed in earlier empirical studies (Liu et al., 2020). The generation of the IV is discussed in the following section.

2.5 Data and Descriptive Statistics

2.5.1 Data

This study uses data from Stats SA GHS, a yearly cross-sectional national survey (Stats SA, 2019). The survey evaluates the living conditions of South African households and tracks the performance and service delivery quality of government initiatives. The GHS gathers information on household and individual characteristics, including education, health, social development, housing, and access to facilities and services. The survey included all household members (i.e., regular residents) across South Africa's nine provinces. Urban samples were not included in this study because our analysis focused on examining the association between the fuel choices of rural households and health. Subsequently, respondents with missing data on the explanatory variables were excluded. The final sample included 23,821 observations.

As approximately 100% of the sampled households used electricity as their primary lighting source, we excluded energy sources for illumination. Alternatively, we focused on the energy sources used for cooking and heating. The treatment variables were measured by asking each household to identify "the main source of energy used for cooking" and "the main source of energy used for heating." Respondents were asked to select from several options. We generated a dummy variable for unclean cooking fuel, indicating 1 for using unclean fuel (e.g., paraffin, wood, coal, and biomass) and 0 for using clean fuel (e.g., electricity and gas). The exact process was used to generate a dummy for unclean heating fuel.

Contrary to previous studies on solid fuel as unclean (Hou et al., 2022; Liu et al., 2020; Alem et al., 2016), we followed the WHO and defined kerosene/paraffin as a polluting fuel by grouping paraffin with unclean fuel (i.e., biomass and solid fuel). A score index was constructed by combining the generated dummies for cooking and heating fuels to investigate the fuel stacking behavior (using multiple fuels), in line with previous literature (Zenelabden and Dikgang, 2022). The variable equals 1 if a household only uses clean fuels, 2 if it uses mixed fuels, and 3 if it relies only on unclean fuels. Additionally, we generated a dummy variable, "fuel binary," from the fuel score index, where 1 indicated the household used mixed or unclean fuels and 0 showed only clean fuels were used, to examine the binary treatment effect and robustness check.

Self-reported health and ARI were the outcome variables. Respondents were asked to rate their general health condition on a scale from 1 (excellent) to 5 (poor). A dummy variable was created from the self-reported health status data to indicate whether a person self-reported a poor health status. It equals 1 if the person chose fair or poor health and 0 otherwise (Oliveras et al., 2021; Quesnel–Vallée, 2007). Respondents were asked if they had suffered from ARI during the past 3 months to measure the other health outcome variable and presented with two options: 1 = yes and 0 = no.

The determinants of fuel choices were selected based on the energy literature (Alem et al., 2016; Liao et al., 2019; Liu et al., 2020; Gould et al., 2020; Lokonon, 2020; Bakhsh et al., 2020; Hou et al., 2022) and public health studies (Chen et al., 2024; Boch et al., 2020; Popovic et al, 2019; Dasgupta et al., 2006). At the individual level, age, education, gender, and marital status were included. At the household level, we included household size, log of household income, whether the dwelling was formal with a modern structure, whether the household had a kitchen, and whether the household used tap water for drinking.

To measure housing quality, we created dummies for the construction materials used in dwellings, including brick walls, mud walls, iron roofs, complex roofs, hard flooring, and soft flooring. According to public health studies (Chen et al., 2024; Boch et al., 2020; Pérez-Hernández et al., 2018; García-Esquinas et al., 2016), housing material type, access to clean water, and cooking in a kitchen were strongly associated with restricted physical functioning, particularly in older people, leading to a high risk of vulnerability; therefore, they were included in this study. In addition, we controlled whether households received FBE as part of the government's national electrification policy to accelerate the transition to clean energy. The FBE program gives poor households 50 kWh of free electricity per month.

We created an instrumental variable independent of the outcome, conditional on covariates, for a robustness check. An instrumental variable that was highly associated with household fuel choices but had no bearing on health was employed. In line with previous studies (see Liu et al., 2017; Liu et al., 2020), this study used the average of the fuel choice of others at the lowest geographic level in our sample, measured by primary sampling. The average fuel choice of others in the PSU is likely correlated with an individual's fuel choice because social norms, peer effects, and shared environmental factors can influence fuel decisions.

Moreover, an additional instrumental variable was generated using the Breusch–Pagan test (Lewbel, 2012). This method is suitable when there is just one available instrumental variable (Hollard and Sense, 2016; Liu et al., 2020). The following equation defines the generated instrumental variable:

$$Fuel_i = Z_i' \alpha_i' + \varepsilon_i', \qquad (2.4)$$

where Zi' is a subset variable of Zi. The residual in Eq. (2.4) had to be heteroscedastic for the generated instrumental variable to be valid. Therefore, we regressed $Fueli$ on each control variable and selected the one with the most considerable chi-square value, showing the strongest heteroscedasticity, defined as the dwelling structure in our analysis.

2.5.2 Descriptive Statistics

Table 2.1 presents the definitions and descriptive statistics of the variables. Approximately 9% of households reported poor health, and 10% reported ARIs. Nearly 53% of the people in our study used unclean fuels for heating and cooking. The average fuel index score is 1.8 (out of 3), indicating that rural families frequently use mixed fuels. The average age of household members is 26 years. The household composition is as follows: 18% of members are married, 45% have senior education, 35% have junior education, and 20% have no education. On average, each household has six members, of whom 54% are females.

Moreover, 79% of households live in a formal dwelling. 88%, 78%, and 88% of the houses were built with brick walls, iron roofs, and tiled flooring. Approximately two-thirds of households have tap water in their dwellings, and 84% have kitchens. Finally, on average, 17% of sampled households receive FBE as part of the government's policy to accelerate the transition to clean energy.

Table 2.1: Description of variables of interest and summary statistics

Variables	**Definitions**	**Mean**	**SD**
Health variables			
Poor health	1: reporting fair or poor health; 0: otherwise	0.094	0.292
ARI	1: reporting acute respiratory illness; 0: otherwise	0.097	0.296
Treatment variables			
Fuel index	1: households use only clean fuels; 2: household uses mixed fuels; 3: households use only unclean fuels	1.804	0.842
Fuel binary	1: if households use unclean or mixed fuels; 0: households use only clean fuels	0.529	0.499
Control variables			
Age	Age (years)	25.66	20.805
No schooling	1: no schooling; 0: otherwise	0.198	0.398
Junior education	1: if the highest degree is junior or primary school; 0: otherwise	0.35	0.477
Senior education	1: if the highest degree is senior high school or higher; 0: otherwise	0.452	0.498
Female	1: female; 0: male	0.538	0.498
Married	1: married; 0: otherwise		
HH size	Number of household members	5.558	3.044
Log income	Log of total household income	6.74	1.03
Structure	1: formal; 0: informal /attached/traditional	0.792	0.406
Bricks wall	1: wall material made from bricks or concrete; 0: otherwise	0.883	0.321
Mud wall	1: wall material made from mud; 0: otherwise	0.075	0.263

Rigid roof	1: The roof material is tile or cement block; 0: otherwise	0.166	0.372
Iron roof	1: roof material made from mud; 0: otherwise	0.779	0.414
Hard flooring	1: floor material made from tiles or ceramic; 0: otherwise	0.878	0.326
Soft floor	1: carpet floor; 0: otherwise	0.047	0.212
Kitchen	1: having a kitchen; 0: otherwise	0.839	0.366
Tap water	1: drinking from tap water; 0: otherwise	0.649	0.477
FBE	1: the household receives free basic electricity from the government; 0: otherwise	0.169	0.375
Fuel other	The proportion of other households surveyed at the PSU level used unclean/mixed fuels in their homes	0.528	0.397

Table 2.2 shows the mean differences in the selected variables by fuel type. Sample means for households using clean, mixed, and unclean fuels are shown in columns 1, 2, and 3, respectively. The F-value and associated statistical significance are shown in the last column of Table 2 to verify whether the means of the selected variables are the same across the three fuel types.

Overall, the findings indicate consistent disparities across the three types. Clean fuel users tend to have higher levels of education and income, be married, and live in formal houses built with brick walls, rigid roofs, and tiled floors, compared with users of mixed and unclean fuels. Approximately 89% of clean fuel users live in formal houses with modern structures, compared with 69.25% of mixed fuel and 72.21% of unclean fuel. Moreover, 13.45% of mixed fuel users reside in homes with mud walls, compared with 10.31% of unclean and 2.72% of clean fuel users.

Notably, mixed fuel users are more likely to have a soft or carpet floor (14.03%) compared to unclean (1.09%) and clean (1.89%) fuel users. These results indicate that individuals who use mixed fuels for household energy needs are more likely to reside in informal, poor-quality housing than their counterparts.

Table 2.2: Mean differences in the selected variables by fuel choices

Variable	**Mean of clean fuel**	**Mean of mixed fuel**	**Mean of unclean fuel**	**F stat.**
Age	26.41	26.54	23.57	46.02***
No schooling	0.181	0.191	0.232	34.81***
Junior education	30.71	37.90	39.75	89.78***
Senior education	51.18	42.91	37.05	177.99***
Female	53.70	53.58	54.19	0.28
Married	19.43	16.84	14.82	31.89***
Log income	7.045	6.57	6.38	1,045.99***
HH size	5.18	5.52	6.23	256.59***
Structure	88.56	69.25	72.21	606.00***
Bricks wall	93.31	82.39	85.19	275.38***
Mud wall	2.72	13.45	10.31	386.92***
Rigid roof	24.92	9.69	8.78	553.50***
Iron roof	70.19	84.78	84.87	381.38***
Hard flooring	94.33	77.82	85.91	539.86***
Soft floor	1.86	14.03	1.09	830.63***
Kitchen	86.24	81.50	82.31	42.01***
Tap water	72.22	60.96	56.17	268.42***
FBE	17.89	18.79	13.38	40.67***
Fuel other	19.07	81.95	83.94	21,129.09***
Obs.	11,230	6,033	6,558	

Note. $^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$.

Moreover, the results indicate that the FBE program has successfully encouraged some households in all categories to use electricity. In addition, 13.4% of households that use unclean fuel for cooking and heating benefit from FBE to meet their basic energy needs, namely lighting. FBE has a positive impact and enables partial transition. However, household electrification has not substantially alleviated multiple fuel use and energy poverty. Despite receiving FBE, poor households cannot utilize electricity as the primary energy source to meet all their needs and still rely on unclean fuels for cooking and heating.

2.6 Results

2.6.1 Determinants of Fuel Choices

Table 2.3 presents the determinants of household fuel choices before examining the estimated impact of household air pollution (HAP). In the Multinomial Logit (MNL) model, we designate clean fuels (e.g., electricity or LPG) as the reference category. This choice is both theoretically and empirically justified: clean fuels are widely recognized as the most desirable option from health, environmental, and development standpoints and are often considered the endpoint of the energy transition. Using clean fuels as the base enables us to interpret the coefficients as changes in the relative log-odds of selecting mixed or unclean fuels compared to clean fuels, conditional on household characteristics and other covariates. This specification aligns with the study's primary objective—to identify the socioeconomic and contextual drivers of continued reliance on non-clean energy sources.

Socioeconomic variables are vital to determining fuel choices. For example, the findings demonstrate that age positively affects the use of mixed and unclean fuels. Consequently, the use of mixed and unclean fuels is often more prevalent among older individuals, probably owing to various factors, including the financial constraints faced by older people, who usually have limited incomes, as well as the cultural and traditional practices that favor the use of biomass fuels in some communities (Qiu et al., 2023; Hou et al., 2022; Wu., 2022; Liu et al., 2020). Furthermore, lack of access to modern energy sources, particularly in rural areas, can exacerbate the reliance on unclean fuels among older populations (Qiu et al., 2023; Puzzolo et al., 2019; Fatona et al., 2013). Senior education negatively affects the likelihood of choosing mixed and unclean fuels over clean fuels. This result supports Wu (2022) and Qiu et al. (2023) findings from China, Gould et al. (2020) findings from India, and Alam et al. (2016) findings from Ethiopia, all demonstrating that better-educated people are more likely to use clean fuel.

Table 2.3: Determinants of household fuel choices[4]

Variables	Mixed fuels	Unclean fuels
Age	0.003***	0.001
	(0.001)	(0.001)
Junior education	0.066	−0.014
	(0.049)	(0.046)
Senior education	−0.172***	−0.436***
	(0.048)	(0.046)
Female	−0.019	0.012
	(0.035)	(0.034)
Married	−0.024	−0.009
	(0.052)	(0.053)
Log income	−0.392***	−0.551***
	(0.019)	(0.019)
HH size	−0.008	0.043***
	(0.006)	(0.006)
Structure	−0.659***	−0.622***
	(0.054)	(0.053)
Bricks wall	0.518***	0.470***
	(0.093)	(0.089)
Mud wall	1.293***	0.832***
	(0.112)	(0.110)

[4] "No schooling" is used as the reference group.

Rigid roof	−0.347***	−0.678***
	(0.095)	(0.092)
Iron roof	0.391***	0.225***
	(0.083)	(0.079)
Hard flooring	−0.262***	−0.707***
	(0.077)	(0.071)
Soft floor	1.536***	−1.449***
	(0.109)	(0.154)
Kitchen	−0.074	−0.130***
	(0.048)	(0.047)
Tap water	−0.402***	−0.553***
	(0.037)	(0.035)
FBE	−0.093**	−0.437***
	(0.045)	(0.047)
Constant	2.281***	4.219***
	(0.200)	(0.194)

Note. $^*P < 0.10$, $^{**} P < 0.05$, $^{***} P < 0.01$; standard errors are presented in parentheses.

An increase in log income is associated with a statistically significant decrease in the probability of choosing mixed and unclean fuels compared to clean fuels. Accordingly, higher-income individuals are less likely to choose mixed or unclean fuels than clean fuels. This finding aligns with previous studies (Qiu et al., 2023; Liu et al., 2020; Zhu et al., 2022), which argue that higher income decreases the likelihood of using unclean fuel. The structure of the dwelling has a considerable influence on fuel use. The use of mixed and unclean fuels decreases with living in formal houses. This finding is consistent with Liu et al. (2020). Moreover, users of mixed and unclean fuels are less likely to reside in homes with rigid roofs constructed from blocks compared to those using clean fuels. Finally, the findings indicate that the role of government policy in accelerating partial transition must be addressed; benefiting from the FBE program significantly decreases the likelihood of mixed and unclean usage.

2.6.2 Result from the Average Treatment Effect

Before examining the estimated treatment effects, we analyzed the distribution of covariates for all covariates when considering multiple treatment options. Figure 1 shows the covariate balancing outcomes for poor health, and Figure 2 shows the ARI results.

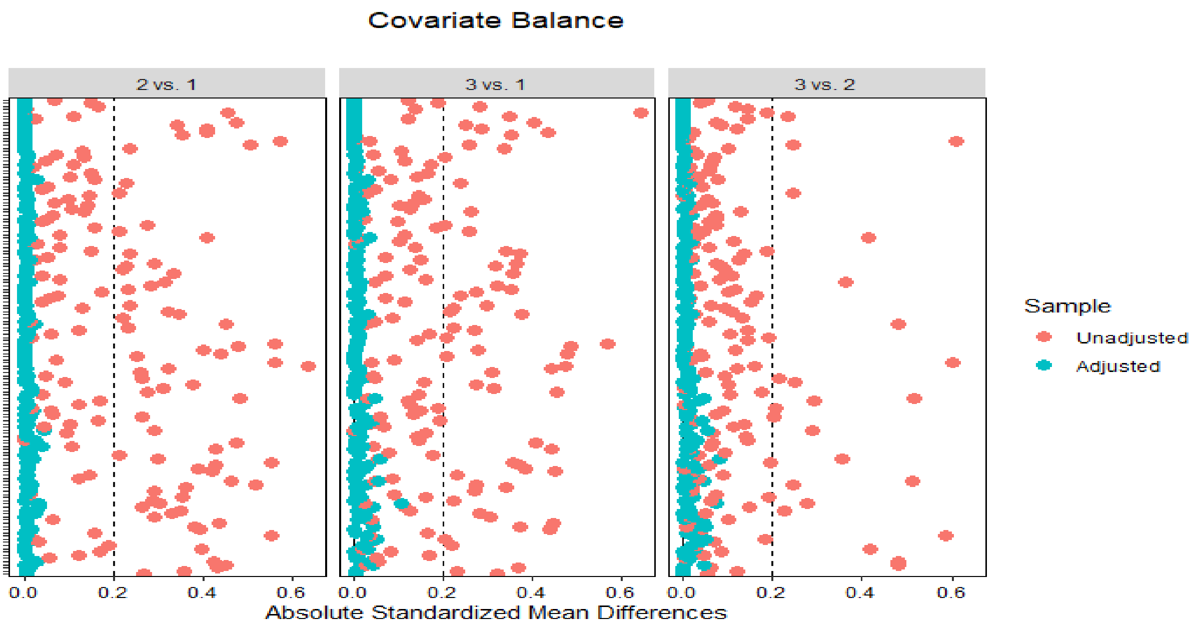

Figure 2. 1: Covariate balance for poor health across all multivalued treatments and covariates[5]

Covariate balance is shown in Figure 1 for poor health and in Figure 2 for ARI, with red and green dots, respectively, before and after applying DML weights to the sample.

[5] *Note*. 1: clean fuels, 2: mixed fuels, and 3: unclean fuels.

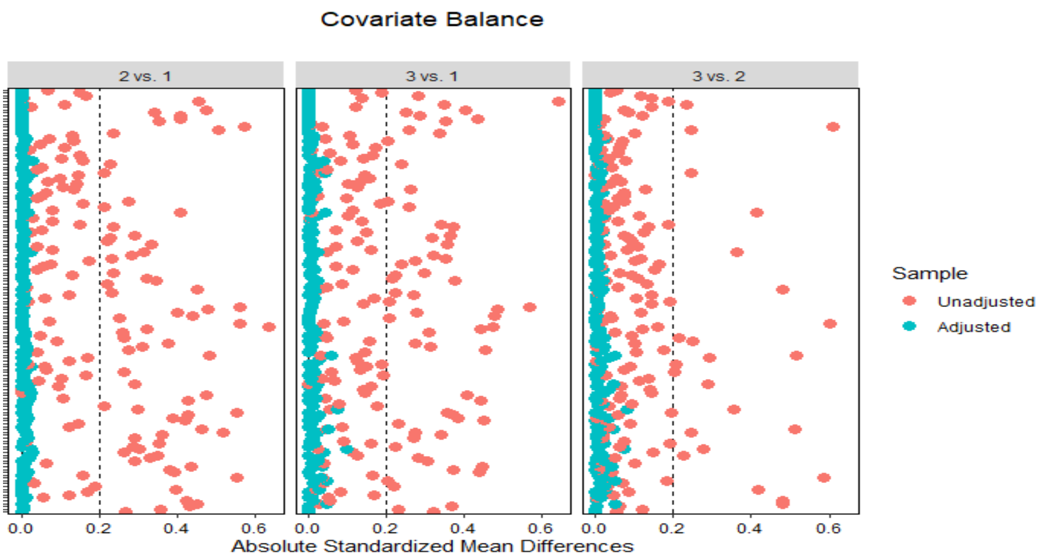

Figure 2. 2: Covariate balance for ARI across all multivalued treatments and covariates

Figures 2.1 and 2.2 illustrate how the DML weights significantly improve variable balance. The green dots are frequently closer to zero than the red dots. The pre-DML comparison shows that multiple covariates are highly imbalanced.

In Table 2.4, the first column presents the results for the binary treatment. The binary treatment results for self-reported poor health status and ARI are positive and significant at 1%. Unclean fuel use is associated with a 2.3% increase in the general poor health status compared with clean fuel use. This finding aligns with previous results (Liao et al., 2016; Liu et al., 2018) that correlated the usage of unclean fuel with poorer self-reported health. Compared with clean fuels, the use of unclean fuels is associated with a 3.2% increase in ARIs. Our findings align with those of Benoit et al. (2020) and Gordon et al. (2014), who observed a positive association between HAP from unclean fuel use and ARI.

The results of the multivalued treatment effects are presented in the last three columns of Table 4. They reveal a clear positive association between the use of mixed or unclean fuels and adverse health outcomes. Specifically, households using mixed fuels are 3% more likely to report poor health and exhibit a 1.9% increase in acute respiratory infections (ARIs) compared to those using clean fuels (Column 2). Similarly, unclean fuel use is associated with a 1.6% increase in self-reported poor health and a 2.5% increase in ARIs (Column 3), relative to clean fuel users. These findings indicate that both mixed and unclean fuels contribute significantly to deteriorating health outcomes.

While a 3% increase in poor health may appear modest, its implications are substantial when viewed at the population level. Even small shifts in health indicators can signal meaningful changes in public health, primarily when they reflect persistent exposure to environmental stressors such as household air pollution. As noted by Nie et al. (2025), such incremental health effects can have broader implications for overall well-being. In the South African context, prior studies have shown that exposure to indoor air pollution from solid fuel use accounted for approximately 1.0–1.7% of national deaths and 1% of total Disability-Adjusted Life Years (DALYs) as of 2012—equivalent to nearly 9,000 deaths and over 200,000 DALYs (Chersich et al., 2018). These figures demonstrate that even relatively small increases in health risks can translate into large-scale public health burdens.

The significance of our results is further supported by existing literature on household fuel use and respiratory illness. For example, Shin et al. (2023) document strong associations between fuel choice and respiratory symptoms in South Africa, including elevated risks of airway inflammation and chronic respiratory conditions among households using paraffin, coal, or wood. As also emphasized by Chen and Kan (2008), chronic exposure to household air pollutants exacerbates the risk of both acute and long-term health conditions, reinforcing the need for targeted interventions.

Table 2.4: Treatment effect of fuel choices on health status

	Binary treatment	**Multivalued treatment**		
Variable	**Unclean *vs.* clean fuels**	**Mixed *vs.* clean fuels**	**Unclean *vs.* clean fuels**	**Unclean *vs.* mixed fuels**
	(1)	**(2)**	**(3)**	**(4)**
Poor health	0.023***	0.033***	0.016**	−0.017***
	(0.005)	(0.005)	(0.007)	(0.008)
ARI	0.030***	0.019***	0.025***	0.007
	(0.005)	(0.005)	(0.006)	(0.006)

Note. **P* < 0.10, ** *P* < 0.05, *** *P* < 0.01; standard errors are presented in parentheses.

The effects of using unclean fuels compared with mixed fuels on health outcomes are presented in Column 4 (Table 2.4). Only poor health is statistically significant; the negative association indicates that households that use mixed fuel have a higher risk of poor health than those that use unclean fuel. The higher health impact observed in households that use mixed fuels compared with the exclusive use of unclean fuels can be explained by considering the interplay between fuel use patterns and housing characteristics. Our descriptive statistics reveal that individuals using mixed fuels are more likely to live in informal houses with carpet flooring and mud walls; this combination may create a particularly hazardous indoor environment (Noorian et al., 2022; Chen et al., 2024). In addition, the use of mixed fuels in households for cooking and heating often leads to incomplete combustion, resulting in higher pollutant levels in the air. The varying combustion properties of different fuels can lead to incomplete burning, releasing a greater quantity of harmful pollutants into the air. These pollutants, including carbon monoxide, PM, and volatile organic compounds, have serious health consequences (Ali et al., 2021).

Furthermore, inconsistent exposure to pollutants from mixed fuel use can be more detrimental than consistent use of unclean fuels. Although switching to cleaner fuels intermittently may seem beneficial, it may not sufficiently reduce pollutant levels. This can lead to periods of high exposure when unclean fuels are used, potentially worsening health.

2.6.3 ATE Results for Subgroup Analysis

The results for the vulnerable groups are presented according to gender and age. ATE results for females and males are provided in Table 2.5, while results based on age group are presented in Table 2.6. The outcomes of the gender-based multivalued treatment effects are presented in Table 2.5. Columns 1 and 4 show the impact of mixed fuel use on female and male health status relative to clean fuel use. The use of mixed fuels has a more negative impact on women and men compared to the use of clean fuels. Using a combination of fuels raises the risk of health issues by 2.9% compared to using only clean fuels. Similar results show that mixed fuel use increases the risk of poor health in males by 3% compared with clean fuels.

Columns 2 and 5 show the effect of unclean fuel use on female and male health outcomes relative to clean fuel use. Results for poor health were significant only in females. Using unclean fuels raises females' risk of poor health by 2.1% compared with clean fuel use. In addition, a significant positive association of approximately 3% was noted between the use of unclean fuel and ARI in females and males.

Table 2.5: Heterogeneous effect of fuel choices by gender

	Female			**Male**		
Variable	**Mixed *vs.* clean fuels** **(1)**	**Unclean *vs.* clean fuels** **(2)**	**Unclean *vs.* mixed fuels** **(3)**	**Mixed *vs.* clean fuels** **(4)**	**Unclean *vs.* clean fuels** **(5)**	**Unclean *vs.* mixed fuels** **(6)**
Poor health	0.029***	0.021**	−0.008	0.030***	0.021	−0.009
	(0.007)	(0.009)	(0.010)	(0.008)	(0.017)	(0.016)
ARI	0.023***	0.027***	0.004	0.023***	0.026***	−0.003
	(0.007)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)

Note. * $P < 0.10$, **$P < 0.05$, ***$P < 0.01$; standard errors are presented in parentheses.

Finally, Columns 3 and 6 show the effect of unclean fuel use on female and male health outcomes relative to mixed fuel use. All results for health outcomes for males and females were statistically insignificant.

Overall, using a mix of fuels and relying solely on unclean fuels for household energy increases the risk of poor health and ARIs compared with clean fuel use. Mixed fuels have a slightly more substantial negative impact than unclean fuels, although the difference is only significant for females.

Table 2.6 examines fuel choices for poor health and ARIs. The results are broken down by age group to identify any age-related vulnerabilities. Columns 1, 4, and 7 show the effects of fuel choices on children, adults, and older people, respectively. The use of mixed fuels is significantly associated with a 0.9% higher risk of poor health in children compared with clean fuel use. The use of mixed fuel requires improvement for adults and older people, with the latter having the highest effect. Adults and older people using mixed fuels are significantly experiencing poorer health than those using clean fuels, with rates of 4.0% and 6.4%, respectively. The results for ARIs are enormously significant only for children, at 1% significance. Consequently, children who live in households that use mixed fuels experience ARIs by 3.3% compared with those who live in households that use clean fuel.

Table 2.6: Heterogeneous effect of fuel choices by age[6]

Variables	**Age ≤ 15**			**16 ≤ Age ≤59**			**Age ≥60**		
	Mixed *vs.* clean fuels	**Unclean *vs.* clean fuels**	**Unclean *vs.* mixed fuels**	**Mixed *vs.* clean fuels**	**Unclean *vs.* clean fuels**	**Unclean *vs.* mixed fuels**	**Mixed *vs.* clean fuels**	**Unclean *vs.* clean fuels**	**Unclean *vs.* mixed fuels**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Poor health	0.009**	0.002	−0.008	0.040***	0.029***	−0.011	0.064**	0.013	0.052
	(0.005)	(0.008)	(0.009)	(0.006)	(0.007)	(0.008)	(0.031)	(0.038)	(0.040)
ARI	0.033***	0.041***	0.007	0.009	0.017**	0.008	0.041*	0.028	−0.012
	(0.009)	(0.010)	(0.011)	(0.007)	(0.007)	(0.009)	(0.021)	(0.023)	(0.024)

Note. *P < 0.10, **P < 0.05, ***P < 0.01; standard errors are presented in parentheses.

[6] The analysis on age is separate and disaggregate the data by age before estimating the effect. In this sub-analysis age is not a covariate to be balanced but a variable that defines heterogeneity.

Columns 2, 5, and 8 show the effects of unclean page fuel use on health outcomes for children, adults, and older people relative to clean fuel use. The use of unclean fuel has a negligible impact on poor health compared with clean fuel use, except for adults, and the results are statistically significant. Unclean fuel use is associated with a 2.9% increase in adults' poor health compared to clean fuel use. Nonetheless, unclean fuel use elevates the risk of ARIs in children and adults by 4.1% and 1.7%, respectively. However, this association is not statistically significant among older people. Finally, the difference between unclean and mixed fuels is not statistically significant for all age groups.

The results for the subgroup analysis by gender and age group are consistent with the overall population results. Mixed fuel use is associated with an increase in poor health compared with clean fuel in all groups, although older people appear to be the most affected group. These health disparities may be partially explained by differences in exposure: women, children, and older adults are more likely to spend extended periods indoors and in closer proximity to cooking areas, thereby experiencing greater exposure to harmful emissions from mixed or unclean fuels. This exposure pathway provides additional intuition for our causal findings. Importantly, our results suggest that a partial transition (e.g., shifting from unclean to mixed fuels) does not lead to health improvements. These findings underscore the importance of transitioning fully to clean fuels to protect household health.

2.6.4 Sensitivity Analysis

Examining the sensitivity of the results to the penalty factor (λ) in LASSO regression is crucial for evaluating their reliability. We apply a data-driven approach proposed by Knaus (2021), which considers sophisticated models along the penalty grid within one SE. The analysis of the results obtained using different penalties indicates that the proposed method produces stable results for plausible penalty terms (Knaus, 2021). The sensitivity analysis results for poor health are presented in Figure 2.3, and the results for ARI are shown in Figure 2.4.

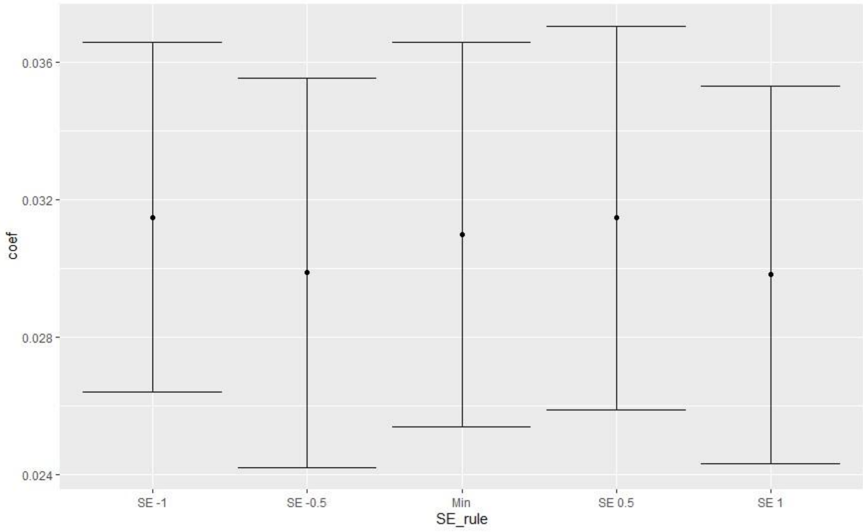

Figure 2.3: Sensitivity analysis for poor health

As model complexity increases, the estimated parameters for poor health status and ARI do not change significantly, indicating that parameter selection does not affect the ATE (Figures 2.3 and 2.4).

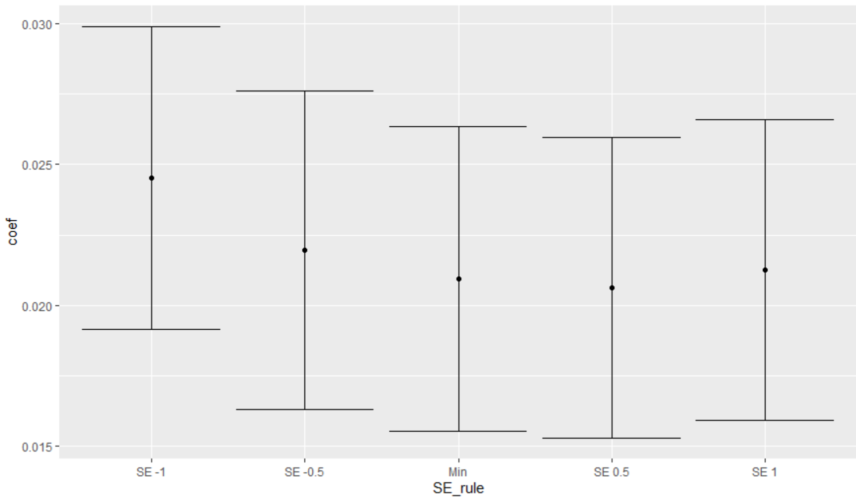

Figure 2.4: Sensitivity analysis for ARI

2.6.5 Robustness Check

We conducted a robustness check to ensure that our findings accurately captured the harmful effects of unclean fuel on health and were not confounded by unobservable factors. Table A2.1 in the Appendix presents 2SLS results. The Kleibergen-Paap rk LM statistic results, used to test for underidentification, are highly significant (P = 0.0000) for poor health and ARI.

Therefore, the models require more identification, meaning more instruments are necessary to determine the parameters. The Cragg–Donald Wald F and Kleibergen–Paap rk Wald F statistics used to assess weak identification are extensive and exceed typical critical values. Accordingly, the instruments strongly correlate with the endogenous variable, indicating model validity. Finally, the Hansen J statistic, used to test for overidentification and the homogeneity of the instruments, was not significant for poor health (P = 0.4783) and ARI (P = 0.7659). This finding supports the assumption that the instruments are likely exogenous; in other words, the chosen instruments do not affect health outcomes through factors other than fuel choices.

2.7 Discussion

Our results show that fuel stacking—mixed use of clean and unclean fuel sources—may have a more detrimental effect on general health than sole reliance on unclean fuels. Conversely, the impact on respiratory illnesses is more severe when using unclean fuels exclusively. This apparent contradiction can be attributed to the complex interplay between fuel type, household characteristics, and health implications.

Households using mixed fuels in our sample are more likely to reside in informal dwellings with suboptimal conditions, such as carpet floors and mud walls. Informal settlements often lack proper ventilation and structural integrity, leading to poor air circulation and the accumulation of pollutants from fuel combustion (Chen et al., 2024; Checkley et al., 2016). This problem may be intensified in mixed-fuel households, as they experience both clean and unclean sources of pollutants. Carpets can act as reservoirs for pollutants, trapping PM and other harmful substances emitted from fuel combustion (Noorian Najafabadi et al., 2022; Becher et al., 2018; Zouk et al., 2002). In mixed-fuel households, carpets may retain pollutants from clean and unclean sources, creating a persistent exposure risk even when cleaner fuels are used. Mud walls, common in informal settlements, absorb and release pollutants, potentially prolonging exposure to harmful substances (Dasgupta et al., 2006). They may also contribute to higher indoor humidity by interacting with fuel pollutants to create secondary pollutants (Noorian Najafabadi et al., 2022; Boch et al., 2020; Dasgupta et al., 2006).

Combining these housing characteristics with mixed fuel use may create a synergistic effect. Pollutants from unclean fuels may be trapped by carpets and absorbed by mud walls. However, using cleaner fuels might create a false sense of safety, reducing ventilation efforts. Accordingly, there may be a higher overall exposure risk to pollutants compared to households that use only unclean fuel, who may be more aware of the need for ventilation (Bruce et al., 2015). Moreover, carpets in informal housing with mud walls reflect a transitional economic state. These households may afford some modern amenities (e.g., carpets) and cleaner fuels, but not consistently. This inconsistent fuel use and poor housing conditions can lead to more variable and potentially harmful indoor air quality (Hanna et al., 2016). Additionally, households that use mixed fuels may have more complex cooking and heating behaviors, potentially leading to more extended periods of fuel combustion and higher overall exposure to pollutants. The false sense of security created by the partial use of clean fuels might also decrease protective behaviors (Ruiz-Mercado and Masera, 2015).

2.8 Conclusion and Policy Recommendations

This study enhances our understanding of household energy transition in rural South Africa by examining the complex interplay between fuel stacking behavior, housing quality, and health outcomes. Employing a DML approach on a sample of 23,821 rural households from the 2019 GHS, we provide nuanced insights into the health implications of various fuel use patterns.

Our findings challenge simplistic narratives of energy transition. In contrast, mixed fuel use is associated with worse health outcomes than exclusive use. This counterintuitive result shows that incomplete transitions may exacerbate rather than mitigate health risks. The health impacts of fuel choices exhibit demographic variations. Older people are particularly vulnerable to the adverse effects of mixed fuel use. However, gender disparities emerge only in the context of exclusive unclean fuel use, which affects females more significantly. The association between mixed fuel use and poor housing conditions (e.g., informal dwellings with carpet floors and mud walls) indicates a complex socioeconomic transition state that compounds health risks.

These findings have critical implications for policy integration, transitional support, targeted intervention, and standards and education. Energy transition policies must be integrated with housing improvement initiatives to address health outcomes effectively. The current siloed approach may require review. Policymakers should recognize mixed fuel use as a potentially precarious transitional state, necessitating sustained support for complete transitions to clean fuel. Age- and gender-specific vulnerabilities require more nuanced, targeted interventions in clean energy promotion and housing improvements. Context-specific indoor air quality standards and community-based education programs that address the unique challenges of rural settings are necessary.

However, this study has the following limitations that future research should address:

1. The analysis does not account for fuel price sensitivity due to data limitations.
2. Direct measurements of pollutant concentrations for different fuel types are required.
3. The spatial layout of dwellings, which could influence exposure levels, should be considered.

Future studies should incorporate these factors to enhance understanding of the relationships between fuel choices, housing conditions, and health outcomes in rural South Africa. Furthermore, longitudinal studies are needed to offer insights into the long-term health effects of different fuel transition pathways.

In conclusion, this study highlights the complexity of the energy transition in developing contexts. It challenges policymakers and researchers to go beyond simple clean/unclean fuel dichotomies and consider the multifaceted nature of fuel stacking behaviors and their health implications. Only through such a nuanced understanding can effective, context-specific policies be formulated to improve health outcomes in rural South Africa.

Chapter Two has illustrated the health ramifications of fuel selection, especially under substandard dwelling conditions. Nevertheless, these selections are profoundly affected by the reliability of the power supply. Chapter 3 analyzes the impact of frequent power outages on household well-being and energy-related decision-making, providing an essential background for comprehending the intricate link between energy access and quality of life (QoL).

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Appendix 1 Exogenous Instrumental Variable Regressions

Table A2.1: Exogenous instrumental variable regressions

Variables	**Poor health**	**ARI**
Fuel final	0.0302***	0.0414***
	(0.00482)	(0.00524)
Age	0.00670***	1.04e-05
	(0.000153)	(0.000122)
Junior education	−0.0613***	−0.0533***
	(0.00509)	(0.00605)
Senior education	−0.135***	−0.0746***
	(0.00548)	(0.00582)
Married	−0.0748***	0.00136
	(0.00685)	(0.00581)
Log income	−0.000812	0.00962***
	(0.00170)	(0.00199)
HH size	−0.00198***	−0.00405***
	(0.000567)	(0.000651)
Female	0.00304	0.0220***
	(0.00334)	(0.00380)
Structure	−0.00429	−0.00815
	(0.00546)	(0.00602)
Bricks wall	0.00659	−0.00384

	(0.00897)	(0.0104)
Mud wall	−0.0104	0.000153
	(0.0109)	(0.0124)
Rigid roof	−0.00572	−0.00365
	(0.00849)	(0.00983)
Iron roof	−0.00321	−0.00215
	(0.00762)	(0.00878)
Hard flooring	0.00865	0.0273***
	(0.00682)	(0.00742)
Soft floor	0.111***	0.0560***
	(0.0129)	(0.0122)
Tap water	0.0111***	0.0181***
	(0.00360)	(0.00403)
Kitchen	−0.00878*	0.000509
	(0.00488)	(0.00547)
FBE	0.00209	0.0112**
	(0.00486)	(0.00527)
Constant	0.00543	0.0442**
	(0.0188)	(0.0224)
Observations	23,821	23,821
R-squared	0.199	0.016

Note. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$; robust standard errors are presented in parentheses.

Hansen J statistics from the two-stage linear square estimation for poor health and ARI are 0.503 ($P = 0.4783$) and 0.089 ($P = 0.7659$), respectively.

Chapter Three: Unplugged and Unhappy? Power Outages and Their Effects on Public Well-Being

Abstract

Power outages pose significant challenges to the well-being of developing countries. This study uses panel data from the GHS (2016–2018) to explore their impact on subjective well-being (SWB) in South Africa. Frequent outages significantly decrease self-reported happiness by applying multidimensional fixed effects models, propensity score matching, and inverse probability-weighted regression adjustment. The adverse effects are particularly severe in rural and metropolitan areas, primarily due to disruptions in cooking routines and meal consistency. These findings highlight the critical need for reliable electricity access to improve quality of life and emphasize the importance of targeted interventions in vulnerable communities.

Keywords: Power outages, subjective well-being, energy insecurity, South Africa, panel data analysis

JEL Codes: I31, Q41, Q48, O13, C23

3.1 Introduction

Access to reliable, clean energy is crucial to human development and well-being. Several developing countries, including South Africa, are focusing on expanding electricity access; however, they often need to pay more attention to the importance of power quality. In Sub-Saharan Africa, nearly a third of grid-connected households experience unreliable power supply; conversely, the situation is better in North Africa (Blimpo and Cosgrove-Davies, 2019).

Since 2007, South Africa has experienced an ongoing energy crisis driven by increased demand and delayed power generation projects. This crisis has led to frequent power outages, commonly called "load-shedding," which profoundly disrupt daily life (Gorjão and Maritz, 2023; Pierce and Ferreira, 2022). By 2019, more than 25% of households experienced multiple weekly outages, with rural areas being disproportionately affected compared with urban centers (StatsSA, 2019; CSIR, 2020). These outages disrupt daily routines and intensify inequalities, leading to diverse impacts on well-being across regions. Urban areas suffer from significant disruptions to traffic, public services, and food storage, whereas rural areas face severe challenges, primarily in water supply and communication (Cole et al., 2018; Klinger et al., 2014).

Although limited research has examined the impact of power outages on SWB, existing studies have reported that unreliable electricity access can have severe psychological and economic consequences. For example, studies from Ghana have stated that power outages result in damaged appliances, income loss, and food spoilage, placing additional stress on households (Nduhuura et al., 2021). In South Africa, although not directly measured in terms of SWB, households expressed a willingness to pay significant amounts to avoid outages, highlighting the negative impact of these disruptions on their QoL (Nkosi and Dikgang, 2018).

This study uses the welfare economics framework to analyze the negative impact of unreliable energy access, particularly power outages, on social well-being. It highlights how these outages create welfare losses by disrupting essential services and disproportionately affecting vulnerable households. In addition, the negative externalities of unreliable energy, such as increased socioeconomic inequality, are examined. By situating the analysis within this theoretical framework, this study emphasizes the need for policy interventions, such as investments in power infrastructure and renewable energy, to improve energy reliability and maximize social welfare.

Furthermore, utility theory was used to investigate the impact of energy reliability on individual well-being. This study highlights the importance of consistent energy access for maintaining comfort, productivity, and living standards. Power interruptions impair utility; they cause discomfort and worry and impede income-generating activities. By framing the problem through utility theory, this study emphasizes the unequal effects of unstable electricity and the necessity for governmental measures to improve infrastructure and equity. In addition, this study contributes to the existing literature by being the first to examine the direct relationship between power outages and SWB in South Africa, as measured by self-reported happiness. Using nationally representative panel data from the GHS conducted between 2016 and 2018, this study offers a detailed analysis of the impact of power outages on well-being at the household and regional levels. This research also addresses potential endogeneity concerns using multidimensional fixed-effect models, PSM, and inverse probability-weighted regression adjustment. It ensures reliable estimates of the effects of power outages.

The impact of power outages on well-being is also explored, revealing that reduced meal consumption and shifts in cooking practices are significant factors. Furthermore, geographic disparities are highlighted, demonstrating that rural and metropolitan areas experience more severe declines in happiness compared with urban and nonmetropolitan regions. By filling this critical gap in the literature, this study underscores the importance of a reliable electricity supply for enhancing public well-being. It provides valuable insights for policymakers into designing interventions that mitigate the adverse effects of power outages, particularly in vulnerable communities.

This study offers essential baseline insights into the effects of power outages on well-being, serving as a benchmark for future research that utilizes data from after 2018. The urgency to address energy insecurity is increasing with the rising frequency of outages since 2019. Consequently, the negative impacts identified in this study may be even more pronounced in the current context.

The remainder of this study is organized as follows. Section 2 presents an overview of energy crises. Section 3 reviews the relevant literature on power outages and well-being. Sections 4 and 5 discuss the data sources and methodology used in the analysis. Section 6 presents empirical results, including the impact of power outages on SWB and an exploration of the underlying mechanisms. Sections 7 and 8 discuss robustness checks and address endogeneity concerns. Finally, Section 9 concludes with crucial policy implications and suggestions for future research.

3.2 Overview of Power Supply Challenges in South Africa

South Africa's energy sector faces various supply and demand issues, worsened by a continued reliance on coal, which makes up about 77 percent of electricity generation. Meanwhile, renewable energy contributes only around 7 percent, despite the country's significant potential in this field (Department of Mineral Resources and Energy, 2019). This dependence on coal raises major sustainability and environmental concerns and restricts opportunities for energy diversification.

Although access to electricity has improved substantially, rising from 58 percent in 1996 to 84 percent in 2020, significant disparities persist across provinces and settlement types (Statistics South Africa, 2020). Urban formal settlements enjoy the highest access rates at 96 percent, while rural formal areas reach 78 percent, and informal rural settlements lag further behind at 68 percent. This uneven distribution highlights ongoing energy access challenges shaped by geography and settlement structure.

Provincial disparities in electricity access are also evident. For instance, the Western Cape reports a 94 percent access rate, while Limpopo and the Eastern Cape fall behind at 74 percent and 76 percent, respectively. These variations are rooted in historical investment patterns, differing levels of economic development, and geographical constraints unique to each region.

From a financial perspective, declining public investment in electricity infrastructure further undermines energy security. Between 2012 and 2018, government investment fell from US$2.33 billion (R35 billion) to US$1.87 billion (R28 billion), reflecting growing supply constraints (National Treasury, 2019). The estimated shortfall between electricity demand and supply ranges between 4,000 and 6,000 MW during peak periods, making scheduled load shedding a necessary but disruptive solution (CSIR, 2020).

System inefficiencies, both technical and non-technical, further aggravate the crisis. Technical losses—stemming from transmission and distribution inefficiencies account for 8–10 percent of electricity generated. Meanwhile, non-technical losses from illegal connections, theft, and billing errors contribute another 10–12 percent, bringing the total system loss to approximately 22 percent (Eskom, 2020). These losses severely constrain supply and heighten the burden on an already fragile power grid.

Eskom, the state-owned utility responsible for most electricity generation, remains at the center of the energy crisis. Its aging, coal-dependent infrastructure is prone to frequent breakdowns and maintenance failures. Since 2007, electricity generation has consistently fallen short of growing demand (Khonjelwayo & Nthakheni, 2021). The situation is worsened by illegal connections, infrastructure vandalism, and system overloads, which result in unplanned outages and add to the 10% of energy lost through non-technical means (Gorjão & Maritz, 2023). Additional losses also arise from meter tampering, inaccurate billing, and the theft of cables.

Frequent blackouts have become an unavoidable part of life in South Africa, profoundly disrupting the daily routines of households nationwide. A consistent electricity supply is required to efficiently perform basic tasks, such as cooking, heating, and refrigeration (Mlambo, 2023). In response to these challenges, numerous households have been forced to invest in alternative power sources, such as generators or batteries, incurring additional costs and health risks, ranging from immediate dangers, such as carbon monoxide poisoning, to temperature-related illnesses, including cardiovascular, respiratory, and kidney diseases (Casey et al., 2020; Lawson, 2022; Ritchie et al., 2024; Marchetti-Mercer et al., 2024). Moreover, power outages reduce productivity, particularly for those working from home (Bantjes and Swartz, 2023; Marchetti-Mercer, 2023). This instability further complicates existing economic challenges, as evidenced by substantial job losses in South Africa's formal sector during the final quarter of 2022, with a decline of approximately 120,000 jobs (Mlambo, 2023).

The severity of South Africa's energy crisis is evident in the staggeringly high number of power outages in 2022, surpassing 200 days (Marchetti-Mercer, 2023). With their high population densities and economic activity, metropolitan areas have borne the maximum brunt of significant disruptions. The financial impact of extended outages is substantial, with estimated daily losses ranging from R150 to R250 million, potentially resulting in an annual loss of R91 billion (Mlambo, 2023).

Frequent power outages in South Africa have profoundly affected food security and household finances. Widespread food spoilage and appliance damage caused by power outages and fluctuations have exacerbated the food insecurity crisis in the country, increasing food prices nationwide (Mlambo, 2023). Consequently, two-thirds of South Africans reported difficulty affording three meals a day, and a substantial proportion found their grocery budgets inadequate to cover their basic needs (Masinga and Madzivhandila, 2023). Moreover, broader societal effects can be observed in education and healthcare. Power cuts have affected schools and hospitals, reduced the quality of education, and compromised medical services (Klinger et al., 2014; Mashiyane et al., 2024).

Consequently, the far-reaching consequences of power outages in South Africa are not merely an economic issue but a multifaceted challenge that touches almost every aspect of society and substantially threatens the nation's progress and well-being.

3.3 Review of the Literature on Power Outages and Well-being

3.3.1 Happiness and Utility

SWB is a complex concept involving an individual's emotional experiences and overall life satisfaction, which has emerged as a critical QoL (Mahoney, 2023). This concept extends beyond economic wealth, recognizing the significant impact of nonmaterial factors, such as social relationships, health, and environmental quality, on happiness (Helliwell et al., 2020). A recent study emphasized the importance of reliable access to basic infrastructure, particularly electricity, in shaping SWB (Koirala and Rahut, 2023).

Happiness and utility are closely related concepts in the theoretical literature, although they emerge from different intellectual, psychological, and economic traditions. Happiness, often conceptualized as SWB, is a multidimensional measure that includes emotional experiences (how people feel) and cognitive evaluations (how satisfied people are with their lives). The literature distinguishes between two primary approaches to happiness: the hedonic approach, which emphasizes maximizing pleasure and minimizing pain (positive and negative emotions), and the eudaimonic approach, which focuses on living a meaningful and purposeful life (Deci and Ryan, 2008; Rayan et al., 2008).

Economically, utility refers to the satisfaction or benefit derived from consuming goods and services (Zenelabden and Dikgang, 2022). In traditional economic models, individuals are considered rational agents who make choices to maximize utility, which is often associated with material consumption. Utility functions quantify the level of satisfaction or happiness derived from these choices. This approach is consistent with the hedonic view of happiness, in which utility reflects pleasure or the absence of discomfort.

The relationship between happiness and utility becomes evident when considering the effects of disruptions, such as power outages. Although traditional economic models focus on the immediate loss of utility resulting from the inability to access electricity-dependent goods and services, a broader view acknowledges the wider impact on well-being. Power outages limit material consumption and affect critical aspects of life, such as health, income, social engagement, and general QoL, all of which contribute to happiness and utility (Praktiknjo et al., 2014).

3.3.2 Immediate Effects of Power Outages on Subjective Well-being

Power outages can directly and immediately impact individuals' SWB, disrupting their daily lives and creating feelings of uncertainty and vulnerability. Recent studies have recognized the profound psychological distress associated with unreliable access to electricity. Ahmed et al. (2023) reported that a substantial number of individuals in Zambia experienced depression directly because of power outages. These people had reported helplessness, decreased social interaction and activity levels, and heightened stress. Moreover, statistical analysis revealed that changes in sleeping patterns caused by power outages were significant predictors of self-reported depression. This finding aligns with research highlighting the role of stress, frustration, and feelings of lack of control in mediating the relationship between power outages and psychological well-being (Marchetti-Mercer, 2023; Marchetti-Mercer et al., 2024).

Power outages can severely limit access to leisure activities, such as watching television or using computers, leading to isolation and boredom, particularly for individuals with limited mobility or social connections (Carlsson and Martinsson, 2007; Praktiknjo, 2014). Outages often evoke feelings of insecurity and vulnerability. Amadi (2015) conducted a study in the Niger Delta and revealed that most respondents viewed power outages as a significant threat to their safety and property. This insecurity is not merely perceived; in the manufacturing sector in Zambia, heightened security costs during power outages highlight the natural connection between power disruptions and compromised safety (Ahmed, 2021).

3.3.3 Secondary Effects of Power Outages on Subjective Well-being

Power outages indirectly undermine well-being, amplify existing vulnerabilities, and create new challenges. The economic repercussions of these outages can be substantial, resulting in income loss, business closures, and increased expenditures for alternative energy sources (Akpeji et al., 2020; Cobbinah and Adams, 2018; Mbomvu et al., 2021; Musabayana, 2023). Therefore, financial strain can significantly impact SWB by generating stress, anxiety, and feelings of insecurity (Kollamparambil, 2020).

Power outages indirectly affect the health of the population by disrupting essential healthcare services. Power interruptions hinder the operation of medical devices and the ability to maintain cold chains for vaccines and medications, posing severe risks to individuals with chronic illnesses or those requiring continuous care (Nduhuura et al., 2021). Additionally, outages often force households to rely on alternative energy sources, such as diesel generators or kerosene lamps, which can increase the likelihood of fire outbreaks and lead to higher levels of air pollution. These factors might lead to environmental degradation, posing further health risks by contributing to respiratory problems and other ailments (Addai et al., 2016; Lawson, 2022).

These indirect pathways, which are less immediately apparent than the direct ones, can have profound and lasting effects on SWB. Economic hardships, health risks, and environmental concerns associated with power disruptions create a complex web of challenges that can significantly undermine individuals' overall sense of happiness and life satisfaction.

3.3.4 Factors Influencing Household Vulnerability to Power Outages

Willingness to pay (WTP) or willingness to accept (WTA) is commonly used to assess the economic impact and costs of power outages on households. These measures reflect the significance households place on consistent electricity access and can indirectly indicate the challenges or losses they face during outages. Abdullah and Mariel (2010) observed that older adults and unemployed individuals in rural Kenya were less willing to invest in reliable electricity. Conversely, larger households were more willing to invest in enhanced electricity reliability. Similarly, Meles (2020) noted that urban households in Ethiopia spend a significant amount each month to cope with power outages and are willing to pay an additional amount beyond their regular electricity bills to improve service reliability.

Studies in Ghana have identified the critical determinants of household WTP for improved electricity service. Amoah et al. (2017) observed in the Greater Accra Region that being male, being married, having an enormous household, and earning a higher income significantly increased the likelihood that households are willing to pay additional amounts for reliable electricity. Similarly, Taale and Kyeremeh (2016) applied Tobit regression in their study of the residents of the Cape Coast Metropolitan Area. They observed that higher income, better education, and marital status were positively associated with WTP for improved electricity reliability. Wealthier and better-educated households exhibited greater WTP for dependable electricity service. Household size was negatively correlated with WTP. However, factors such as age, homeownership, and monthly electricity expenses did not show any significant relationship with WTP.

Nkosi and Dikgang (2018) conducted a study in South Africa to estimate the welfare implications of power outages. They presented respondents with eight scenarios and employed a random parameter panel Tobit model to account for zero WTP and cross-sectional heterogeneity. Their findings revealed that WTP increases with the outage duration, indicating that South African households significantly value uninterrupted power supplies.

Although existing research has explored the various impacts of power outages, a significant gap in understanding their direct effects on SWB remains to be addressed. Our study adds to this gap by examining the direct impact of outages on happiness. It used nationally representative panel data to provide new insights into energy policies.

3.4 Data Sources and Variable Descriptions

This study used data from Stats SA GHS, an annual survey that assesses household living standards across the country. The GHS collects comprehensive information on household and individual characteristics. The dataset used in this study covered the years 2016–2018, as data on power outages were not collected in subsequent years. This dataset offers a nationally representative sample, enabling a thorough analysis of the impact of power outages on people's well-being. Notably, GHS does not explicitly track load shedding—planned power outages implemented to balance electricity demand and supply. Alternatively, the dataset focuses on general service delivery quality, including electricity supply, and reports only on unplanned outages experienced by households.

However, one limitation is that the data could be more recent. Since 2018, South Africa's energy crisis has changed significantly, with load-shedding becoming more frequent and intense. This limitation restricts the study's ability to capture recent trends in power outages and their potential impacts on household well-being and happiness. Despite this limitation, the study remains relevant. Rigorous methods, such as fixed effects and PSM, reduce potential biases and allow us to draw meaningful insights applicable beyond the data's time frame.

The 2016–2018 GHS dataset was chosen based on its unique longitudinal structure, enabling the estimation of rigorous panel data models, such as multidimensional fixed effects (MDFE) modeling. Although more recent data would improve the study's relevance over time, the core relationships between energy reliability and well-being will probably not change significantly. Future studies could build on these findings by incorporating more up-to-date data, considering the worsening energy crisis. We constructed a balanced panel dataset using, for example, the method proposed by Zenelabden and Dikgang (2022) to ensure robust analysis. This approach used unique identifiers for dwellings and household heads to track consistent units over time, resulting in a balanced panel comprising 47,427 observations.

The outcome variable, SWB, measured households' happiness based on the question, "Are you happy, the same, or less happy with life than you were ten years ago"? The answer was measured using a three-point score (1: less happy, 2: the same, and 3: happy). Subsequently, we converted this into a binary variable, where 1 represents feeling "happier" and 0 denotes feeling "the same" or "less happy." Our primary interest was to understand whether outages reduce happiness. Hence, a binary outcome provides a straightforward interpretation of the impact of outages. This approach to measuring SWB through self-reported happiness aligns with earlier studies (Lucas and Diener, 2009; Zhang et al., 2020). To assess the unreliability of the electricity supply, households were asked whether their electricity had been cut off without warning in the past 3 months, despite paying bills or purchasing prepaid electricity; if the answer was yes, the frequency was the same. Outages were classified into three categories based on frequency: 1 for no outages, 2 for 1–6 outages, and 3 for more than seven outages. This reclassification was implemented due to the small number of households that reported frequent outages, exceeding seven.

We carefully incorporated a set of control variables to improve the robustness of our estimations and reduce potential bias from unobserved variables. At the individual level, we accounted for factors such as the age of the household head and its squared term (to capture nonlinear effects), along with education, employment status, and marital status (Mensah, 2024; Nduhuura et al., 2021; Stone et al., 2010; Stutzer and Frey, 2006). Household characteristics included income and size (Mensah, 2024; Nduhuura et al., 2021). Furthermore, recognizing the importance of community-level influences on well-being, we controlled for key crucial characteristics, including noise and outdoor air pollution (Shepherd et al., 2010; Weinhold, 2013; Zhang et al., 2020; Zhang et al., 2022).

Table 3.1: Summary of descriptive statistics for core variables

Variables	Description	Mean	Standard deviation
Dependent variable			
Happy	Whether happier with life (1: happier, 0: otherwise)	0.294	0.455
Core independent variable			
Power outage	Frequency of power outage (1: no outages, 2: occasional outages, 3: frequent outages)		
Occasional power outages		0.205	0.403
Frequent power outages		0.021	0.144
Individual characteristics			
Age	Age of householder in years	50.05	15.69
Age^2	Age square of householder	2,751.82	1,669.27
Primary education	Whether the householder has a primary education (1: yes, 0: otherwise)	0.226	0.418
Senior education	Whether the householder has a secondary education or higher (1: yes, 0: otherwise)	0.664	0.472
Married	Whether the householder is married (1: yes, 0: otherwise)	0.345	0.475
Employed	Whether the householder is employed (1: yes, 0: otherwise)	0.525	0.499
Household (HH) characteristics			
HH size	Total number of members in the household	3.695	2.401
Log income	Log of the total income of the household	8.560	1.249
Community characteristics			
Noise pollution	Whether there is noise pollution in the householder community (1: yes, 0: otherwise)	0.149	0.356
Outdoor pollution	Whether there is outdoor pollution in the householder community (1: yes, 0: otherwise)	0.195	0.396

Table 3.1 presents the variables and summary statistics. Approximately 29% of respondents reported being happy with life, highlighting a moderate level of SWB across groups. Unplanned power outages affected a large portion of the sample. Approximately 21% experienced occasional outages, whereas 2.1% experienced frequent power disruptions. The average age of respondents was 50 years, and educational attainment levels indicated varied backgrounds. Approximately 23% had completed primary education, whereas the majority (66 %) had achieved an education level equivalent to or above senior high school, reflecting an educated population. Nearly 35% of the respondents were married, and 53% were employed. In addition, 15% of the respondents experienced noise pollution, and 20% experienced outdoor air pollution within their communities.

Given this study's focus on the relationship between power outages and happiness, it was crucial to begin with a preliminary correlation analysis. A correlation diagram was used to visually explore the potential relationship between the two variables before undertaking the regression analysis. This initial step helped identify any observable patterns or trends that could inform subsequent empirical investigations. Figure 1 shows a comparison of happiness levels among respondents from 2016 to 2018. Data are presented as percentages, with blue bars representing those who reported being happy and red bars representing those who were unhappy.

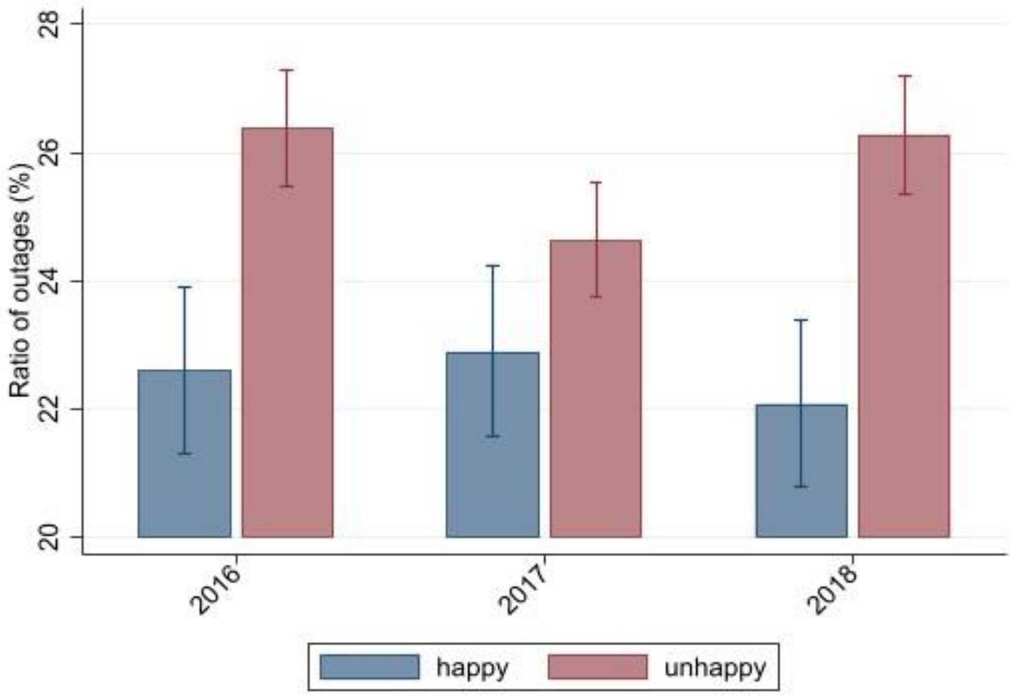

Figure 3.1: Tracking happiness over time based on power outage frequency

Figure 3.1 shows a consistent and significant gap between the proportion of happy and unhappy individuals, with the percentage of unhappy respondents being consistently higher. The graph indicates a potential negative correlation between power outage frequency and self-reported happiness from 2016 to 2018. Higher outage ratios generally correspond with lower happiness, particularly in 2018. Consequently, frequent power disruptions can significantly affect SWB.

3.5 Methods

To examine the relationship between power outages and household SWB, we employed an MDFE approach, which extends the traditional fixed effects approach by including two or more high-dimensional fixed effects, such as individual, time, and group, in a single estimation. The MDFE is beneficial for addressing endogeneity concerns and omitting observable and potential confounding factors that remain constant over time within a particular dimension, thus providing more robust estimates (Balazsi et al., 2018). Moreover, this approach was selected because it particularly suits our research question. It can handle the complex, multilevel structure of our data, where households are nested within geographic areas and observed over multiple periods (Balázsi et al., 2024).

When analyzing the effect of power outages on SWB, unobserved variables can vary across several dimensions, such as households, periods, geographic regions, and socioeconomic groups. Household-specific factors, such as access to alternative energy sources and financial resilience, can shape the impact of outages on SWB. Simultaneously, regional factors, such as local infrastructure, economic conditions, and community support networks, may also play a significant role. Additionally, the timing of outages, including critical periods such as heatwaves, public holidays, high social activity, and work-related stress, can influence emotional well-being, making temporal elements another essential factor to consider.

A standard fixed effects model may allow us to control for unobserved household characteristics that remain stable over time. However, this model may not capture variability in unobserved regional or time-specific factors that can shape SWB outcomes. For example, if one region experiences more frequent or prolonged outages due to poor grid infrastructure, the effects on well-being in that area could be systematically different from those in a region with fewer outages. Similarly, time-specific shocks, such as economic downturns or significant political events during the study period, can influence household well-being independently of power outages.

The MDFE model allows for unobserved household, regional, and time fixed effects. The specification includes household fixed effects (γ_i) to control for time-invariant household characteristics, year fixed effects (δ_t) to account for temporal national-level shocks affecting the entire country, and province-by-year fixed effects (θ_{ijt}) to control for province-specific time shocks.

In our specification, we incorporate household fixed effects (γ_i) to control for unobserved, time-invariant characteristics at the household level, fixed effects at the year level (δ_t) to account for national time trends common to all provinces, and province-by-year interaction terms (θ_{jt}) to account for province-specific time trends. This specification is crucial for a host of methodological reasons:

The year fixed effects represent average unobserved shocks standard to all provinces (e.g., national economic cycles, macroeconomic conditions, policy changes, etc.). However, provinces in South Africa develop along heterogeneous paths that are conditioned by the timing of the infrastructure projects, the implementation of provincial policies, and localized economic shocks. Province-by-year fixed effects account for these province-specific, time-varying factors that would otherwise bias our estimates.

Second, the use of this strategy mitigates the concern regarding possible omitted variable bias due to unobserved province-time-specific effects. To illustrate, the provinces of the Western Cape and Gauteng may have had different dynamics regarding economic growth, infrastructure investments, or the timing of power outages compared to the provinces of Limpopo or the Eastern Cape. Had we not included the province-by-year controlling variables, such dynamics could result in bias in our coefficients on power outages.

Third, this specification adheres to the standard econometric conventions for a panel dataset that has both a geographic and temporal dimension (Balázsi et al., 2024). The use of both year and province-year fixed effects is not overkill, but rather a necessary procedure: year effects account for common trends, and province-year effects account for differential trends across provinces. This specification has been utilized in past research on the regional heterogeneity of infrastructure effects (Zehang, 2023; Mensah, 2024).

Among these, the province-by-year fixed effects are particularly relevant because they control for patterns of heterogeneous economic development across regions, the timing of infrastructure openings and closings, heterogeneous policies, and heterogeneous local shocks that evolve differently across space and time. This specification accounts for temporal variation in exposure to outages over time within households, while controlling for the common national trend and provincial-time trends.. We model power outages as a linear function of well-being expressed through the following baseline regression equation[7]:

$$Y_{ijt} = \alpha_0 + \beta_1 Outage_{ijt} + \beta_2 Z_{ijt} + \gamma_i + \delta_t + \theta_{ijt} + \varepsilon_{ijt}, \qquad (3.1)$$

Y_{ijt} is the dependent variable (SWB) for household head 'i' in province' j' during period 't'. α_0 is the constant term, Outage $_{ijt}$ is the power outage, Z_{ijt} is a vector of time-variant control variables composed of individual, household, and community characteristics, γ_i are the household fixed-effects, δ_t are the year fixed-effects, θ_{ijt} are the province-by-year fixed effects absorbing province-specific time trends in economic development, infrastructure investment, and policy implementation that may affect well-being independently. The idiosyncratic error, ε_{ijt}, is assumed to be independently distributed. The robust standard errors are clustered at the household level to protect against serial correlation and heteroskedasticity within household observations over the periods.

3.6 Empirical Findings on Power Outages and Well-Being

3.6.1 The Influence of Power Outages

Table 3.2 presents the baseline findings on the relationship between power outages and SWB, as specified by Eq. (1). A stepwise regression approach was used to identify the outage effects, beginning in Column 1 (Table 3.2) with no control variables. Columns 2–4 add individual, household, and community characteristics. Column 5 includes an interaction term combining the province- and time-fixed effects. Column 6 explores robustness using a panel random effects model. However, the results of the Hausman test (Prob > $chi^2 = 0.000$) indicate that the panel fixed effects model provides a more reliable approach for this analysis.

Across all models, occasional and frequent power outages were associated with significantly reduced happiness. In Models 1–5, occasional outages were linked to approximately a 3% reduction in happiness. However, a notable difference emerges in Model 6, the panel random effects (RE) model, where the effect becomes more pronounced, indicating that occasional outages reduce happiness by approximately 5%. This consistent negative impact underscores

[7] The model was estimated using Stata 18, employing the regfe command to account for unobserved individual-specific effects.

how even intermittent electricity disruptions can negatively influence individuals' day-to-day experiences and perceptions of well-being.

Frequent power outages demonstrate an even more substantial negative impact on happiness. The coefficient for frequent outages remained remarkably consistent across Models 1–5, showing an approximate 10% decrease in happiness. This strong effect persists in the panel random effects model (Model 6), further highlighting that frequent disruptions to electricity infrastructure have a consistently more detrimental impact on people's quality of life. This dose-response relationship, where more severe (frequent) outages lead to a larger adverse effect, intuitively supports a causal interpretation.

The observed difference in the magnitude of the impact of occasional outages between the fixed effects (Models 1-5, implicitly) and the random effects (Model 6) models warrants further discussion. When the random effects (RE) estimates are larger in magnitude (more negative) than the fixed effects (FE) estimates, as seen with occasional outages, it often suggests that between-household variation might be exacerbating the observed effect.

In simpler terms, this could mean that households that systematically experience more outages also tend to have systematically lower well-being for reasons partly unrelated to the outages themselves. For example, these households might reside in areas with poorer infrastructure, lower socioeconomic status, or other unobserved, time-invariant characteristics that predispose them to both more outages and lower happiness. In technical terms, this indicates a potential correlation between the regressor (outage frequency) and unobserved factors, thereby violating the strict exogeneity assumption necessary for random effects estimates to be unbiased.

Given this, the fixed effects results (implicitly captured in Models 1-5 when analyzing the panel data structure) are generally considered more trustworthy if we suspect such correlations. The fixed effects approach explicitly controls for all time-invariant unobserved household-specific characteristics, thereby providing a more conservative and likely more robust estimate of the causal impact. Using both RE and FE models strengthens the credibility of our results. Many researchers treat the fixed effects estimates as a conservative or lower-bound estimate of the true effect. So if outages still appear to reduce well-being even after controlling for all stable household differences, the real impact could be even larger. The consistent gap between the RE and FE results reinforces our suspicion that unobserved, time-invariant factors matter—and it supports our decision to rely on a robust methodological approach.

Table 3.2: Estimation of well-being effects from power outages: A benchmark regression

Dependent variable, whether happier with life						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Occasional power outages	−0.029***	−0.03***	−0.029***	−0.029***	−0.029***	−0.051***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)
Frequent power outages	−0.097***	−0.097***	−0.096***	−0.096***	−0.095***	−0.092***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.014)
Age		−0.006***	−0.006***	−0.006***	−0.006***	−0.007***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Age^2		0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education		−0.012	−0.013	−0.013	−0.013	0.017**
		(0.012)	(0.012)	(0.012)	(0.012)	(0.008)
Senior education		0.002	0.003	0.003	0.003	0.052***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.008)
Married		0.049***	0.05***	0.05***	0.05***	0.071***
		(0.009)	(0.009)	(0.009)	(0.009)	(.005)
Employed		0.074***	0.079***	0.079***	0.079***	0.106***
		(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
HH size			0.001	0.001	0.001	0.004***
			(0.002)	(0.002)	(0.002)	(0.001)
HH Log income			−0.016***	−0.016***	−0.016***	−0.004**
			(0.003)	(0.003)	(0.003)	(0.002)
Noise pollution				−0.028***	−0.027***	−0.041***
				(0.008)	(0.008)	(0.006)
Outdoor pollution				−0.013*	−0.014*	−0.01*
				(0.008)	(0.008)	(0.006)
Constant	0.303***	0.401***	0.526***	0.529***	0.534***	0.368***

	(0.002)	(0.039)	(0.044)	(0.044)	(0.044)	(0.025)
Observations	47,427	47,427	47,427	47,427	47,427	47,427
R-squared	0.53	0.533	0.534	0.534	0.535	0.051

*Standard errors are in parentheses. ***P < 0.01, **P < 0.05, * P < 0.1.* [8]

Although people experience a slight dip in happiness as they age, the rate of decline slows down over time. This finding supports the well-established U-shaped relationship between age and life satisfaction observed in several studies (Blanchflower and Oswald, 2008; Stone et al., 2010). Being married is associated with approximately 5%-7% higher levels of happiness than being unmarried, which is consistent with previous studies (Diener et al., 2000; Stutzer and Frey, 2006). In addition, employment has a strong positive association with happiness, implying that having a job is an essential factor in SWB. This finding underscores the importance of employment in SWB, consistent with the findings of McKee-Ryan et al. (2005) and Ohtake (2012).

Household income shows a small but negative association with happiness, which indicates diminishing returns to income in terms of happiness, supporting the Easterlin Paradox (Easterlin, 1974; 2001). This theory proposes that once the basic needs of individuals are met, further increases in income may not significantly improve life satisfaction and could even slightly reduce it because of additional pressures or expectations. Noise pollution has a negative and significant impact on happiness; individuals exposed to high noise pollution levels report approximately 3%–4% lower happiness. This finding highlights the detrimental effects of environmental factors on well-being (Weinhold, 2013; Shepherd et al., 2013).

The findings reveal that occasional and frequent power outages significantly reduce happiness, with the latter having a particularly strong negative impact. These results remain consistent across various specifications, indicating that improving the reliability of electricity could have a notable positive impact on happiness, particularly in regions that experience frequent outages.

[8] No outage and no schooling are the reference categories for power outages and education, respectively, and, therefore, omitted from the estimation.

3.6.2 Robustness Tests of the Regression Results

Two methods were applied to confirm the robustness of the estimated results: replacing the core independent variable and adjusting the model specification. The empirical findings are summarized in Table 3.3. Given the binary nature of the dependent variable, the analysis employed fixed effects and random effects panel logit models.

Table 3.3: Robustness testing: Duration of power outages and their effect on happiness

	Replacing model		**Replacing X**
	(1) Logit FE	**(2) Logit RE**	**(3)**
Power outages	−0.028***	−0.038***	—
	(0.006)	(0.005)	
Interruption ≥ 12 h	—	—	−0.037***
			(0.014)
Control variables	Yes	Yes	Yes
Household-fixed effect	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes
Province- × time-fixed effect	Yes	Yes	Yes
Observations	20,853	47,427	47,427

Standard errors are in parentheses; ***$P < 0.01$, **$P < 0.05$, * $P < 0.1$

Logit FE: fixed effect; Logit RE: random effect

Columns 1 and 2 of Table 3.3 show the average marginal effects, demonstrating that the coefficient for power outages remains negative and statistically significant regardless of the model used. These results align with the baseline regressions, reinforcing the robustness of the findings.

Second, we provided an additional estimate by changing the core independent variable to the duration of power outages lasting 12 hours or more (0: no; 1: yes). The prolonged outage was used as a proxy for blackouts. Column 3 of Table 3.3 illustrates that prolonged outages significantly reduce happiness, further highlighting the detrimental impact of more prolonged power interruptions. This result reinforces the findings from the baseline model that shorter, frequent outages negatively affect SWB. The results underscore the importance of electricity reliability in sustaining household happiness and QoL.

To further validate our results, we have performed an additional analysis using an ordered probit model, which considers the ordered nature of the happiness variable (less happy, same, happier). In the main study, we have considered happiness as a binary variable; however, this method retains the original grouping of the survey response and serves to validate our results.

Table 3.4: Marginal Effects of Power Cut on Happiness (Ordered Probit Model)

Outcome Category	**Marginal Effect**	**Std. Error**
Less Happy (1)	0.038***	0.0047
Same (2)	-0.002***	0.0003
Happier (3)	-0.037***	0.0045
Control variables	Yes	
Observations	47,427	

Standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01

Results from the ordered probit model, reported in Table 3.4, provide strong support for the findings obtained using an alternative estimation technique. Loss of power increases the likelihood of respondents identifying themselves as "less happy" by 3.8 percentage points and decreases the probability of respondents identifying themselves as "happier" by 3.7 percentage points. The symmetric effects across categories further validate the binary coding of the variable, indicating that power outages tend to push respondents into lower categories of happiness. Overall, these results provide further evidence of the robustness of our results across various model specifications and measures of subjective well-being.

3.6.3 Addressing Endogeneity Issues

Our study rigorously addresses the challenge of endogeneity, which can arise from unobservable factors influencing both power outages and household well-being. We tackle this primarily through the MDFE (Multi-dimensional Fixed Effects) model, which effectively controls for omitted, time-invariant unobservable characteristics at various levels. Additionally, we mitigate potential measurement bias in our core variables by employing a proxy variable approach where necessary.

While the MDFE model accounts for unobservables, we also recognize that observable characteristics, such as employment status, could introduce selection bias. For instance, households with employed members might systematically report higher well-being, irrespective of outage experiences. If households that experience outages also differ systematically from those that don't, based on such observable traits (like employment), a direct regression approach alone might not fully isolate the true impact of outages. This is because these pre-existing differences could confound the observed effect.

To address this specific concern of selection bias on observable characteristics, our study employs Propensity Score Matching (PSM) and Inverse Probability Weighting Regression Adjustment (IPWRA). The core rationale behind PSM is to create comparable "treatment" (households experiencing outages) and "control" (households not experiencing outages) groups by matching them based on their propensity score. This score represents the probability of a household experiencing an outage, given its observable characteristics (e.g., employment status, income, household size). By matching households with similar propensity scores, we ensure that the estimated effect of outages on happiness is less likely to be confounded by differences in these observable factors, thereby strengthening our causal inference.

In our application of PSM, we utilized nearest neighbor (NN) matching with a caliper of 0.05 and a 1:4 matching ratio. This specific ratio was chosen to minimize the mean squared error, as supported by research (Zheng, 2023). The propensity scores themselves were estimated using a logit model. By integrating PSM and IPWRA, we enhance the robustness of our findings, providing a more accurate reassessment of how power outages impact happiness while explicitly accounting for potential biases related to observable household characteristics. Furthermore, the original treatment variable for power outages was converted into a binary variable for PSM, indicating whether a household experienced a power outage (1: yes; 0: no).

Table 3.5 presents the PSM results and a comparison of the balance between the treated and control groups across variables. The findings revealed a significant improvement in balance after matching. For example, the mean difference in age between the groups reduced substantially, with its bias dropping from −35.5% to 2.8%, representing a significant 92.1%

reduction. The *t*-tests indicate that several previously significant differences became nonsignificant after matching, although some variables, such as "primary education," remained slightly imbalanced ($P = 0.040$). The variance ratios for most variables improved, approaching the ideal value of 1. The overall balance statistics provide strong evidence of the effectiveness of the matching process. The results indicate that the PSM approach successfully mitigated numerous preexisting differences between the groups, allowing for a more accurate assessment of the impact of power outages on SWB.

Table 3.5: Balance test for matched variables using nearest neighbor matching

Variables	**Unmatched (U)**	**Mean**			**%reduct.**	***t*-test**	
	Matched (M)	**Treated**	**Control**	**Bias (%)**	**Bias**	**T**	***P* > *t***
Age	U	45.817	51.298	−35.5		−32.19	0.00
	M	45.82	45.385	2.8	92.1	2.08	0.03
Age^2	U	2,331.3	2,875.1	−33.6		−29.98	0.00
	M	2,331.5	2,299.8	2	94.2	1.49	0.13
Primary education	U	0.22988	0.2252	1.1		1.02	0.308
	M	0.22981	0.21811	2.8	−150.0	2.06	0.04
Senior education	U	0.67141	0.66228	1.9		1.76	0.07
	M	0.67147	0.69391	−4.8	−145.6	−3.53	0.00
Married	U	0.28049	0.36433	−18.0		−16.12	0.00
	M	0.28052	0.26826	2.6	85.4	2.01	0.04
Employed	U	0.61187	0.49984	22.7		20.55	0.00
	M	0.61183	0.61878	−1.4	93.8	−1.05	0.29

HH size	U	3.1807	3.8462	−28.3		−25.43	0.00
	M	3.1809	3.1484	1.4	95.1	1.07	0.28
HH Log income	U	8.5056	8.576	−5.7		−5.14	0.00
	M	8.5056	8.5092	−0.3	94.8	−0.22	0.82
Noise pollution	U	0.2056	0.13264	19.6		18.74	0.00
	M	0.20553	0.19192	3.6	81.3	2.50	0.01
Outdoor pollution	U	0.26998	0.17316	23.5		22.39	0.00
	M	0.26991	0.25635	3.3	86.0	2.26	0.02

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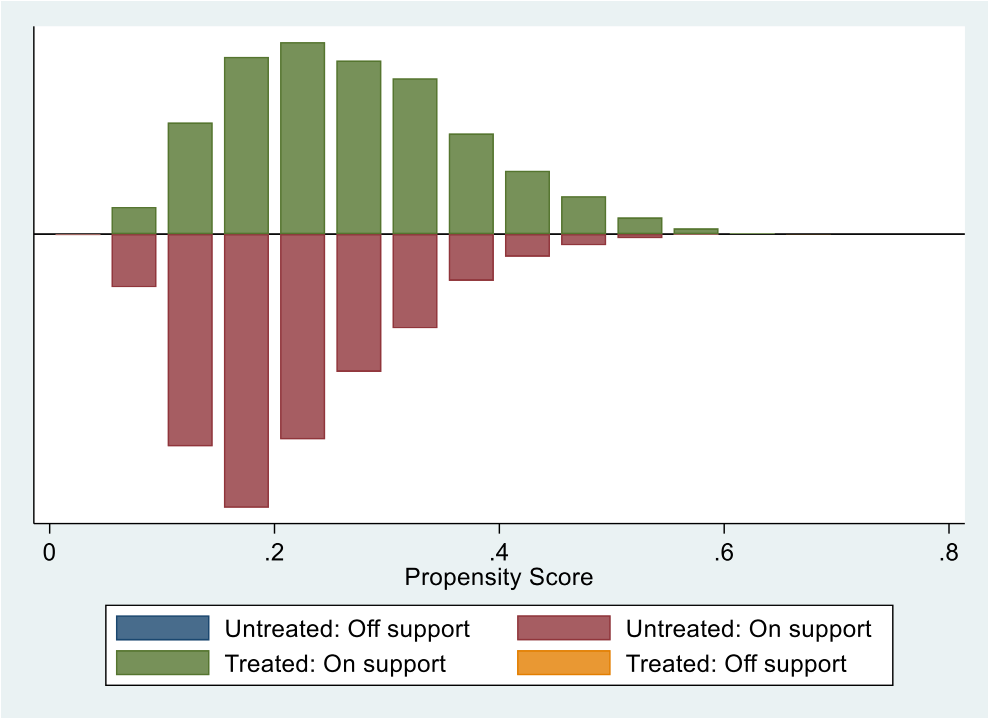

Figure 3.2: Comparison of propensity scores between treated and untreated households

Figure 3.2 shows the distribution of propensity scores for the treated and untreated groups in the PSM analysis, illustrating the level of overlap and matching support. The *x*-axis represents the range of propensity scores, which are the estimated probabilities of receiving treatment based on observable covariates, and the *y*-axis indicates the frequency of observations. Green bars denote treated observations, and red bars indicate untreated observations “on support” (matched). The green and red bars overlap, indicating a balanced match, particularly within propensity scores ranging from 0.1 to 0.5, which suggests reliable comparisons between the two groups. Notably, no “off support” observations exist, meaning that all treated units have suitable matches among the untreated group, which ensured that treatment effects could be reliably estimated

Table 3.6: Power outages and well-being: PSM and IPWRA results[9]

Estimators	Whether happier with life		ATT/ ATET	SE/ RSE	T-value/ Z-value	Common support	
	Treat	Control				Treat	Control
NN matching within caliper (n = 4, r = 0.05)	0.270	0.304	−0.033***	0.005	−5.87	10,748	36,674
Radius matching (r = 0.05)	0.270	0.302	−0.032***	0.005	−6.39	10,748	36,674
Kernel matching (bandwidth = 0.03)	0.270	0.302	−0.032***	0.005	−6.33	10,748	36,674
Local linear regression matching	0.270	0.301	−0.031***	0.006	−4.54	10,748	36,674
IPW regression adjustment	—	—	−0.032***	0.005	−6.43	—	—

***P < 0.01, **P < 0.05, *P < 0.1

[9] SWB: Subjective well-being; PSM: Propensity score matching; IPWRA: Inverse probability weighting regression adjustment; NN: Nearest neighbor; IPW: Inverse probability weighting.

Table 3.6 presents an analysis of power outages, including their impact on happiness, yielding compelling results across various matching techniques. These methods, including NN matching, radius matching, kernel matching, local linear matching, and inverse probability weighting (IPW) regression adjustment, indicate a consistent and statistically significant adverse effect of power outages on happiness. These findings suggest that individuals experiencing power outages report lower happiness levels than those not affected by such disruptions. In particular, the happiness level of those affected by power outages was approximately 3% lower. This effect remained remarkably stable across all matching techniques employed.

The robustness of these results is noteworthy. Although each matching method exhibited different assumptions and strengths, the conclusions for all methods were similar. This consistency across methodologies strengthens the reliability of the finding, revealing that the observed negative impact of power outages on happiness is not an artifact of any specific statistical approach but rather a genuine effect.

3.6.4 Community-Level Measure of Power Outages

To address potential endogeneity concerns arising from the reliance on self-reported measures of both power outages and well-being, we conducted a crucial robustness check. We constructed a more objective measure of outage exposure by calculating the average proportion of households reporting any power outage within each Primary Sampling Unit (PSU) for every given year. This community-aggregated variable significantly reduces concerns about individual-level reporting biases or reverse causality, providing a less subjective proxy for local power supply reliability. Our re-estimated fixed effects model, utilizing this aggregated measure, thus offers a robust confirmation of the observed relationship between power outages and well-being, mitigating key endogeneity concerns.

Table 3.7: Fixed Effects Regression of Well-being on PSU Level

Dependent Variable Happiness	
Outages others	-0.03*** (0.014)
Control Variables	Yes
Household fixed effect	Yes
Time fixed effect	Yes
Province x Time-fixed effect	Yes
Observation	47,427
R squared	0.534

Robust standard errors clustered at the household level are presented in parentheses; *** p<.01, ** p<.05, * p<.1

Table 3.7 presents the results of the fixed effects regression using the average level of outages reported at the PSU (community) level as the primary explanatory variable. The coefficient on community-level outages is negative and statistically significant, indicating that higher average outage intensity in a community is associated with a substantial reduction in household well-being. This robust effect is observed after accounting for various individual socioeconomic factors and comprehensive household, time, and province-specific fixed effects.

3.7 Mechanisms Linking Power Outages to Well-Being

Theoretical and practical considerations influenced our choice of electric stove use and frequency of meal preparation as the mechanisms of interest in our primary study. These variables capture the most direct and visible effects of electricity disruptions on daily life in South Africa.

A direct behavioral connection exists between the use of an electric stove and the potential for an electric power cut, as it will instantly turn off all electric cooking devices. This is a significant concern in South Africa, where electric cooking is a standard for all households, irrespective of income level. Loss of access to electric cooking may lead households to seek out alternative cooking fuels (such as gas, paraffin, or wood) that may be more expensive, inconvenient, or unsafe (Bekker et al., 2008).

The frequency of meal preparation encompasses additional logistical issues besides varied cooking practices. A decrease in the frequency of meal preparation during an outage may signify one or more of the following: an inability to store and preserve foods without refrigeration; a break in the normalization of food shopping due to the cessation of business; greater complexity in food preparation using alternative cooking methods; or economic factors that drive the alternative fuel to be costlier. This variable thus indicates not only direct logistical difficulties but also potential implications for food security—an issue of relevance in low- and middle-income countries, where food security is already tenuous (Davis, 1998).

We recognize that psychological stress, lost productivity, social exclusion, health effects, and other mediating channels are possible candidates to be at least as necessary. However, our dataset did not permit the inclusion of these variables. The selected indicators we propose are concrete and quantifiable channels through which outages translate into everyday life impacts, and they present immediate policy implications about the real-world effects of an unstable electricity supply. Table 3.8 presents findings from a mechanism test exploring the effect of power outages on cooking habits and meal frequency, potentially impacting SWB. The results are significant at the 1% level of significance.

Table 3.8: Examining meal preparation patterns during power outages

	Dependent variable, whether happier with life	
	(1) Electric stove	**(2) Less meals**
Power outages	−0.045***	0.037***
	(0.004)	(0.005)
Control variables	Yes	Yes
Household-fixed effect	Yes	Yes
Time-fixed effect	Yes	Yes
Province- × time-fixed effect	Yes	Yes
Observations	47,427	47,427
R-squared	0.653	0.578

Standard errors are in parentheses; ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$

The results in Table 3.8 indicate that power outages were associated with decreased use of electric stoves, indicating that people were forced to change their cooking methods during blackouts. Thus, in response to the frequent power outages, households may have had to reduce their reliance on electric cooking methods. They may shift toward alternative cooking technologies, such as gas stoves or other fuel sources that are less affected by power outages.

Conversely, a positive and significant effect of the power outage was observed in the reduction in the number of meals, which might signal broader economic challenges, such as raising food prices and making regular meals more difficult to afford. The combination of logistical difficulties in cooking without electricity and potential economic pressures can create a situation where households face increased challenges in maintaining regular meal consumption.

These results demonstrate that power outages are significantly associated with cooking methods and meal frequency, potentially disrupting everyday household routines and access to electrical cooking appliances. This finding helps explain some mechanisms through which power outages might affect SWB, highlighting the tangible impacts of unreliable electricity supply on daily life, household decision-making regarding cooking equipment, and potentially even broader economic and food security issues.

3.8 Additional Insights: Regional and Temporal Variations

Table 3.9 presents the results of the association between power outages and whether individuals across different geographic areas reported being happy with their lives. The data extracted were categorized into urban and rural areas and metropolitan and nonmetropolitan regions. The findings consistently show a negative relationship between power outages and happiness, with the impact being statistically significant at the 1% level across all studied areas.

In rural areas, power outages were associated with a 4.3% decrease in happiness, reflecting the most substantial negative effect among the broad categories. Urban areas showed a slightly smaller but substantial effect, with power outages associated with a 3.5% reduction in happiness. Furthermore, we observed significant differences between metropolitan and nonmetropolitan areas. In highly urbanized metro areas, power outages were associated with a 4.6% decrease in happiness, the most significant negative impact observed across all subcategories. The nonmetropolitan areas showed a minor effect, with power outages associated with a 2.9% decrease in happiness.

These results reveal that although power outages universally decrease happiness, the magnitude of this effect varies across geographic settings. The impact is most pronounced in highly urbanized metropolitan areas. However, nonmetropolitan regions seem less affected, although they still experience a notable decrease in reported happiness.

Table 3.9: Geographic patterns of power outage frequency and well-being

	Happiness			
	Geographic characteristics			
	Rural	Urban	Metropolitan	Nonmetropolitan
Power outages	−0.043***	−0.035***	−0.046***	−0.029***
	(0.011)	(0.008)	(0.011)	(0.009)
Control variables	Yes	Yes	Yes	Yes
Household-fixed effect	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes
Province- × time-fixed effect	Yes	Yes	Yes	Yes
Observations	18,147	29,280	16,176	31,251
R-squared	0.512	0.563	0.486	0.562

Standard errors are in parentheses; ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

Variations in the impact of power outages across these diverse settings may be attributed to factors such as differences in infrastructure quality and resilience, varying levels of reliance on electricity for daily activities and economic functions, or differing community expectations regarding power reliability. Rural areas may require more robust infrastructure, resulting in more frequent or longer-lasting outages, with fewer alternative resources or activities available during outages. However, metropolitan areas demonstrated the most substantial negative effect among all categories, surpassing rural areas. This could reflect the high dependency on electricity in metropolitan environments for work and leisure activities and potentially higher expectations for reliable services. Therefore, power supply disruptions might be felt more acutely in the fast-paced, highly connected lifestyles typical of metropolitan areas.

3.9 Conclusion

Far from being merely inconveniences, power outages cast a long shadow on human well-being. Disrupting essential services, economic activities, and daily routines can negatively impact physical and mental health, financial stability, and overall QoL. This intricate relationship between power, reliability, and well-being is particularly significant in South Africa, where ongoing power challenges underscore the urgent need to understand and address the multifaceted impacts of power outages on the population.

Although the existing literature investigated the impact of power outages on various aspects of life, including unemployment, health, and economic consequences, this study explicitly focuses on their effect on SWB. We analyzed the impact of power outages on well-being using an MDFE model, along with IPWRA and PSM methods, leveraging nationally representative data from the 2016–2018 Stats SA GHS. Our rigorous methodological approach addressed potential endogeneity issues, yielded reliable estimates, and revealed the complex relationship between power outages and well-being.

Furthermore, this study examined regional disparities in South Africa to provide valuable insights into the varying impacts of power outages across regions. The findings consistently demonstrated a clear negative impact of power outages on individuals' reported happiness. This effect was statistically significant across all models and estimation techniques used, highlighting the robustness of the relationship. Occasional outages notably decrease happiness, whereas frequent outages cause a more severe decline. These effects remained consistent after controlling for individual, household, and community factors and province- and time-fixed effects. Our mechanistic analysis demonstrates the effect of power outages on daily life and overall happiness.

Our findings indicate a twofold impact of power outages. Outages limit cooking ability because stoves become nonfunctional. They may also reflect broader economic challenges, such as rising food costs and making regular meals more difficult to afford. Consequently, this impact contributes to more significant challenges in maintaining consistent meal consumption. This direct influence on basic daily activities provides a clear pathway through which power outages significantly diminish QoL and, consequently, happiness.

The impact of power outages on happiness varies across geographic areas. Rural and highly urbanized metropolitan areas are the most severely affected by power outages, exhibiting a marked decrease in joy. Although nonmetropolitan urban regions are also negatively affected, they experience a less pronounced reduction in happiness. These variations indicate that the connection between reliable power and SWB is shaped by factors such as infrastructure quality, dependence on electricity, and community expectations, which vary across geographic contexts.

These results have significant policy implications for addressing the negative impact of power outages on QoL, particularly in rural and highly urbanized areas. Policymakers should prioritize investments and initiatives that improve the reliability and stability of electricity supply, including the following:

- Upgrading and expanding power infrastructure: Modernizing existing power grids, expanding transmission and distribution networks, and investing in new generation capacity is crucial for ensuring a dependable electricity supply.
- Promoting renewable energy sources: Renewable energy sources, such as solar, wind, and hydropower, should be integrated into national energy systems to enhance energy security and sustainability. These sources can reduce reliance on fossil fuels and support Africa’s commitment to the global energy transition under the Paris Agreement.
- Improving energy efficiency: Implementing policies and programs that encourage energy efficiency practices in households and industries can help reduce overall electricity demand and alleviate pressure on the power grid.
- Targeted interventions for vulnerable populations: Recognizing the disproportionate impact of power outages on vulnerable households, policymakers should develop targeted interventions to support those most affected, including subsidies for energy-efficient appliances, access to backup power solutions, and community-based initiatives to enhance resilience.
- Enhance access to clean and reliable cooking solutions: Policymakers should prioritize expanding access to clean cooking options, such as Liquefied Petroleum Gas (LPG) stoves and solar cookers, while supporting decentralized energy systems, including solar home systems and minigrids. These initiatives are particularly vital for ensuring dependable power backup in rural areas.

However, this study has several limitations. This study focuses on the association between power outages and SWB without exploring other potential mediating factors or long-term consequences. Future studies should examine long-term effects within a dynamic framework that requires the availability of detailed longitudinal microdata, tracking individuals’ physical and mental health, economic status, and overall QoL over extended periods, even after restoring the power supply. Accordingly, we could understand the long-term consequences of power disruptions, including their lingering effects and cumulative impact over time.

The GHS dataset does not explicitly track load-shedding events or their intensity. It focuses on general service delivery. Although this limitation means the study cannot fully capture the differences between planned and unplanned outages, the findings are still robust. They provide an essential foundation for further exploration of these dynamics in future research.

Future studies should expand on this study by using more recent datasets or alternative sources, such as energy utility records, real-time outage tracking systems, or household surveys that precisely measure the impacts of load-shedding. The integration of these data can enable researchers to better understand the changing relationship between energy insecurity and well-being.

The evidence of the detrimental effects of power interruptions on well-being raises inquiries about household adaptation measures. Chapter 4 examines a critical response, the use of PV systems as an alternative energy source, analyzing the facilitators and obstacles to this shift.

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Chapter Four: Responding to Power Outages: Solar PV Adoption and Lighting Choices in South African Households

Abstract

In South Africa's ongoing energy crisis, marked by recurrent and prolonged power outages, households increasingly seek alternative energy sources, primarily for lighting. This study examines the impact of power outages on household energy choices, focusing on solar photovoltaic (PV) adoption and lighting fuel options. A random effects multinomial logit model with data from Stats SA GHS (2016–2018) revealed that extended outages significantly increase the likelihood of adopting solar energy and reduce reliance on the national grid. In addition, outages increase the possibility of using solar energy for lighting. Income influences this shift, supporting the energy ladder hypothesis, and gender plays a significant role. Female-headed households are more likely to adopt solar energy, indicating that women, who are often responsible for managing household resilience during power disruptions, prioritize reliable energy sources. Although some families choose renewable energy, others revert to less environmentally friendly options, underscoring the need for policies that promote accessible and sustainable energy solutions to support a just energy transition during ongoing power challenges.

Keywords: Energy choices, solar adoption, power outages, multinomial logit model

JEL Codes: Q41, Q42, Q48, O13, D12

4.1 Introduction

South Africa has a compelling energy paradox. Although more than 90% of households have access to electricity, consistent with Sustainable Development Goal 7 (StatSA, 2021), the country remains heavily reliant on coal, which generates 85% of its electricity (Akinbami et al., 2021). Accordingly, South Africa is the largest emitter of carbon dioxide (CO_2) in Africa, contributing 11% of the continent's total emissions in 2021 (IEA, 2023). Furthermore, electricity demand is projected to more than double by 2050, driven by population growth and industrialization, intensifying environmental and energy challenges (Wright et al., 2017).

South Africa's energy crisis is rooted in Eskom, a state-owned power utility, and its reliance on aging coal-fired power plants. Since 2007, frequent breakdowns and rolling blackouts have disrupted the electricity supply nationwide (Lawrence, 2020). The economic consequences of these power outages have been substantial, costing the country an estimated $100 billion over the past decade. They have also strained households by raising costs and hindering productivity (Lawrence, 2020; Burgess et al., 2020).

The energy ladder hypothesis provides a valuable framework for understanding how households adapt their energy consumption patterns in response to changing circumstances, such as unreliable electricity grid supply (Mensah & Adu, 2015). This hypothesis proposes that as households experience rising incomes and improved access to technology, they tend to transition from traditional biomass-based energy sources to more modern, efficient, and cleaner alternatives. This transition is evident in South Africa, with households shifting from conventional fuels (e.g., wood and coal) to electricity for various needs (e.g., lighting and cooking).

However, the frequent load shedding and unreliability of electricity grids in South Africa significantly hinder households' progress on the energy ladder. Faced with power interruptions, rational consumers often seek immediate alternatives, such as acquiring backup power solutions (e.g., generators). Although generators provide a readily available source of electricity during outages, they represent a step down on the energy ladder because they rely on fossil fuels and negatively impact the environment. A more sustainable response would be to adopt renewable energy technologies, such as solar home systems and lighting, which offer cleaner and more cost-effective energy solutions in the long term. However, the high upfront costs of solar technologies and the limited availability of subsidies pose significant barriers for numerous South African households, preventing their widespread adoption.

Studies on how households adapt their energy choices during power outages are limited. For example, Nogoma et al. (2018) and Koirala and Acharya (2022) examined the response of households in Zambia and Nepal to power shortages, primarily through energy stacking—the simultaneous use of multiple fuel sources. In Zambia, households adopted different strategies, such as fuel-switching, load-shifting, and conservation. However, reliance on biomass and backup generators increased in Nepal. These coping mechanisms underscore the importance of diverse energy sources in managing load shedding. However, neither study explored the role of solar energy in these transitions. Given its widespread availability in Africa and South Asia, solar power is a sustainable alternative to traditional strategies involving biomass and generators. This omission underscores a critical gap in our understanding of how solar technologies could transform household energy practices in regions with frequent power shortages.

This study extends existing research by investigating the adoption of solar energy as a critical response to unreliable electricity supply, particularly during the energy crisis in South Africa. Panel data from GHS (2016–2018) were used to examine the influence of power outages on household transitions toward renewable energy sources, focusing on gender dynamics and lighting fuel choices (IEA, 2019). Recent studies have indicated that gender dynamics significantly influence household fuel choices during energy transition, with women often preferring cleaner fuels than men (Adusah-Poku et al., 2023; Chen et al., 2024; Totouom, 2024). This preference is likely driven by the disproportionate health, time, and economic burdens that women often bear due to the use of unclean fuels.

Given the persistent energy crisis in South Africa, characterized by high electricity costs and unreliable supply, understanding how female-headed households adapt their energy choices is crucial. These households may face unique challenges and constraints that influence their decisions regarding energy sources, such as solar PV systems. By analyzing gender-specific energy choices, this study provides valuable insights into informing policies and programs that support households, particularly women-headed ones, in transitioning to reliable and sustainable energy solutions.

This study makes several significant contributions. First, it provides new insights into the impact of power outages on household decisions in terms of solar energy adoption. Second, this study extends the analysis beyond lighting fuel choices by examining household decisions about the primary power source. This broader approach offers a detailed understanding of the shift toward renewable energy by considering the full range of energy options available to households rather than focusing solely on lighting. Third, this study acknowledges the role of gender dynamics, particularly in female-headed households, and investigates the influence of these factors on energy choices. Finally, a panel multinomial logit (MNL) model with both random and fixed effects is used to address unobserved heterogeneity across households and over time, enhancing the robustness of the findings on energy transition.

4.2 South Africa's Energy Landscape

Eskom, the largest electricity producer in Africa, generates approximately 90% of South Africa's electricity, with 93% of its generation coming from coal-fired power plants (Baker & Phillips, 2019). Consequently, Eskom plays a significant role in the country's energy landscape and its heavy reliance on coal. Within the three-tiered government structure (national, provincial, and local/municipal) in South Africa, municipalities contribute to delivering energy services to residents. They are responsible for maintaining the energy infrastructure, connecting new customers to the grid, and establishing pricing and subsidy programs for low-income consumers (Euston-Brown & Borchers, 2018).

Electricity distribution is a crucial function for municipalities in South Africa, which are responsible for supplying 40% of the country's electricity, with Eskom managing the remaining 60%. Municipalities purchase electricity in bulk from Eskom at wholesale prices, adding a markup before selling it to end users (StatsSA, 2015b). The revenue generated from these sales is used to cross-subsidize the provision of other essential municipal services (StatsSA, 2015a). Revenue from middle- to high-income electricity consumers is crucial for funding electricity access and new connections for low-income households (Baker & Phillips, 2019).

Between 2008 and 2016, the average price of electricity in South Africa increased by more than 200% (Baker & Burton, 2018). The inclining block tariff structure in municipalities has disproportionately impacted high-income consumers during these tariff hikes. Under this system, customer payment increases with the electricity consumed. Consequently, high-income consumers, who typically use more electricity, incur increased costs and are more likely to seek alternative energy sources (Cape Town Electricity Services, 2015).

South Africa has a total domestic energy generation capacity of 58,095 megawatts (MW). Coal remains the dominant energy source, comprising over 80% of the country's energy mix. However, the 2019 IRP indicates a planned phase-out of 24,100 MW of conventional thermal power sources, primarily coal, over the following 10–30 years. Despite recent investments in renewable energy technologies, including wind, PV, and concentrated solar power, their combined contribution to the total energy mix is only approximately 14% (CSIR, 2023).

The South African government has implemented various programs and policies to promote the transition toward renewable energy. In 2018, South African REIPPPP signed 27 power purchase agreements for utility-scale operations. The government has updated the IRP to improve the country's unstable and failing energy sector. The REIPPP has three main objectives: reducing CO_2 emissions, enhancing generating capacity, and fostering economic development. It emphasizes increasing the use of natural gas, keeping the nuclear industry operational, and emphasizing social inclusion and a "just transition plan" to renewable energy sources.

Furthermore, municipalities have implemented several policies and projects to promote the transition to renewable energy in the residential sector. In 2007, the Free Basic Alternative Energy policy was introduced to assist unelectrified households with subsidized alternative safe energy, such as solar home systems and fire gel. However, the adoption of this subsidy should be higher; only 10% of informal unelectrified households nationally receive the subsidy (StatSA, 2014). Moreover, the Department of Energy and Eskom launched a nationwide solar water heater program between 2008 and 2014, which included high- and low-income households. The former was fully subsidized for low-income families and partly subsidized to approximately 20% of the capital cost for high-income households (Baker & Phillips, 2019). However, after almost half a million solar geysers were installed, the program was terminated because it was considered ineffective in increasing demand (SEA, 2015).

Despite the government's efforts in setting policies for renewable energy transition, the country's power sector remains challenged and lacks formal policies that foreground renewables in the utility grid. In 2008, South Africa experienced multiple periods of energy crisis or load-shedding. Chronic underinvestment in the electricity sector led to escalating power prices and a shortage of capacity during peak demand periods, resulting in planned and unplanned blackouts, which had severe implications on households and the entire economy (Walsh et al., 2021; Toto, 2022). The country witnessed the worst load-shedding in 2022, with an outage duration of 3,773 h or 11,529 GWh of energy shed (CSIR, 2023). Power outages remain chronic in South Africa. The inadequate supply of power and high electricity costs have encouraged numerous households to seek alternative sustainable options or go off-grid to meet their daily needs.

4.3 Literature Review

The literature has examined the factors influencing household lighting fuel choices and the adoption of solar energy, offering valuable insights into the key drivers of sustainable energy transition. This review synthesizes findings from various studies to provide a comprehensive understanding of the determinants of solar adoption and to identify significant gaps in current research.

4.3.1 Lighting Fuel Choice

Several studies have noted that socioeconomic factors significantly influence lighting fuel choices. Lay et al. (2013) and Best (2023) examined the determinants of household lighting choices in Kenya, including solar options. They identified income, education, and asset ownership as critical factors in solar adoption. In addition, Baek et al. (2020) in Kenya and Fentie et al. (2023) in Ethiopia supported the energy ladder hypothesis, revealing that the probability of choosing modern lighting sources, including solar, increases with higher income and education levels.

Gender disparities in lighting fuel choices were also explored. Behera and Ali (2017) reported that female-headed households in Malawi, Ethiopia, and Tanzania were more likely to adopt renewable energy sources for lighting than male-headed households. This finding is consistent with the findings of Baek et al. (2020), who observed a positive relationship between female-headed households and the choice of modern lighting options, including solar.

Earlier studies have presented mixed results on the role of age in lighting fuel use. Some researchers have observed a negative relationship between age and the use of clean fuels (Baiyegunhi & Hassan, 2014; Gebreegziabher et al., 2012; Behera et al., 2016; Baek et al., 2020; Fentie et al., 2023). Conversely, others have noted a positive relationship between age and clean fuel use, such as electricity and LPG (Gupta & Köhlin, 2006; Rao & Reddy, 2007; Özcan et al., 2013; Danlami et al., 2019).

Education is consistently a significant factor in the adoption of clean energy sources. Different studies from India (Narashimha & Reddy, 2007; Reddy & Srinivas, 2009) and across African countries (Lay et al., 2013; Behera & Ali, 2017; Fentie et al., 2023) have identified a positive correlation between education levels and the likelihood of using electricity and solar energy for lighting.

4.3.2 Gender Dynamics and Household Energy Transition

The existing literature has highlighted the crucial contribution of women to household decision-making in driving the energy transition. Qualitative studies have emphasized the importance of women's preferences and priorities in household energy choices (Fingleton-Smith, 2018; Musango, 2022). In addition, quantitative studies have acknowledged that women-headed households are more likely to use clean fuel (Johnson et al., 2019; Adusah-Poku et al., 2023). However, the underlying incentives behind the female-driven clean energy transition, particularly in the context of solar adoption, have not been fully explored.

Female-headed households may prefer clean energy solutions, such as solar PV, due to interconnected factors. Women are often more concerned about environmental issues and the long-term health impacts of traditional energy sources. This heightened environmental awareness has likely contributed to their preference for cleaner alternatives. In several developing contexts, women disproportionately shoulder energy-related tasks, such as collecting firewood or managing household energy consumption (Mohideen, 2012, 2013). Furthermore, female-headed households are often more economically vulnerable and sensitive to fluctuations in energy prices. The long-term cost savings and price stability associated with solar energy make it attractive, providing a sense of energy independence and security (Aryal et al., 2019).

Recent studies have highlighted the role of gender dynamics in household energy decisions. For example, Chen et al. (2024) in China and Totouom (2024) in Cameroon reported that households where women have greater bargaining power are more likely to adopt cleaner cooking fuels, such as gas and electricity. This shift provides well-documented benefits to women, including saving time, improving health, and enhancing environmental quality (Lee et al., 2023). Women's preference for cleaner fuels often drives household energy consumption toward options that prioritize their health and convenience, particularly in households where women have significant decision-making authority (Choudhuri & Desai, 2020). These findings underscore the importance of considering gender dynamics to understand better household energy choices and the potential for solar energy adoption, particularly in the context of extended power outages.

4.3.3 Solar Adoption and Renewables Transition

Scholars have conducted extensive research to understand the factors determining households' intention to adopt solar energy. However, empirical evidence on actual adoption behavior remains limited. These factors can be broadly categorized into economic, demographic, personal, social, environmental, technical, regulatory, and market-related (Shakeel et al., 2023).

Economic considerations, such as high installation costs and the potential for monetary benefits, have been identified as significant drivers of solar adoption (Shakeel & Rahman, 2018; Alrashoud & Tokimatsu, 2019; Sackey et al., 2020; Jayaraman et al., 2017). The relationship between income and solar adoption is complex. Although some studies have reported that higher income and wealth encourage adoption (Sigrin et al., 2015; Kowalska-Pyzalska, 2018), others have argued that lower-income individuals may be more motivated to adopt solar energy to reduce costs (Bashiri & Alizadeh, 2018).

Personal characteristics and demographic factors, such as education, prior knowledge, and age, also influence the willingness to adopt solar energy (Yuan et al., 2011; Kwan, 2012; Zander et al., 2019). In addition, household characteristics, including size and home ownership, can influence solar adoption decisions (Bashiri & Alizadeh, 2018; Schaffer & Brun, 2015; Briguglio & Formosa, 2017).

The market environment, including dependable vendors and installers, as well as ongoing technological advancements, can significantly influence households' intentions to adopt solar sources (Tsantopoulos et al., 2014; Abdullah et al., 2017; Mohandes et al., 2019). Several studies have shown mixed results regarding the impact of environmental concerns and power system reliability on solar adoption (Leenheer et al., 2011; Opiyo, 2016; Jamil & Islam, 2023).

Although the literature provides valuable insights, several fundamental limitations remain. Several studies have investigated intentions rather than actual behavior, have used cross-sectional data that fail to capture the dynamic nature of energy decisions, and have not comprehensively examined demand- and supply-side factors. This study aims to address these gaps by employing a nationally representative panel dataset from South Africa GHS (2016–2018) to analyze solar adoption behavior over time while accounting for individual heterogeneity.

4.4 Research Methodology

The energy ladder hypothesis is widely used to examine energy transition in developing countries. We tested the existence of an energy ladder in the context of household energy choices for lighting and the adoption of solar PV systems. The energy ladder hypothesis assumes that households shift to clean, sustainable energy sources as income increases. In addition to income, other variables, such as power supply reliability and demographic composition, can play a significant role in the energy transition**.** In line with Lay et al. (2013), we rely on the random utility framework to capture household energy choices. We express the utility derived from a particular selection of energy type as an indirect utility function of power interruption and sociodemographic characteristics, including income, age, and education. Thus, the proposed conceptual framework can be represented as follows:

$$U = f(O, X), \qquad (4.1)$$

where *U* represents the satisfaction (utility) households gain from selecting specific energy sources, O denotes the occurrence of power outages, and *X* is a vector of sociodemographic variables that can affect energy choices.

To test the conceptual framework outlined in equation (1), this study employs a panel MNL model to investigate the factors influencing household adoption of clean and renewable energy sources. This model is selected because households facing power interruptions use multiple fuel options, rendering a binary logit model unsuitable for this analysis. The MNL model allows for the examination of numerous discrete choices, where each household *i* faces a set of energy choices j at time *t*. The underlying assumption is that each energy source provides a certain level of utility, and a household rationally chooses the source that maximizes its utility.

Following the approach of Fentie et al. (2023), this study categorizes energy sources for the main power supply into three categories based on their position in the energy ladder: other sources (0), in-house electric meter (1), and solar PV (2). Similarly, lighting fuel choices are categorized as dirty fuels (0), generators (1), electricity (2), and solar (3). This categorization allows for analyzing households' transition between different energy sources along the energy ladder. This study uses a panel dataset of households observed over 3 years (2016–2018). The empirical model is represented as follows:

$$V_{ijt} = O'_{ijt}\gamma_j + X'_{ijt}\beta_j + \mu_{ij} + \varepsilon_{ijt}, \qquad (4.2)$$

where V_{ijt} is utility derived from choosing specific energy sources that maximize the utility of household i at time t. O'_{ijt} represents the power outage that lasted for more than 12 h. X'_{ijt} is a vector of the explanatory variables influencing the households' energy choices. β_j is the vector of the parameter particular to fuel j, which is estimated using the maximum likelihood. μ_{ij} is the unobserved household's specific effect associated with energy source j. ε_{ijt} is an independent and identically distributed random error term. We estimate the random effects of MNL, which assumes that the explanatory variables are exogenous conditional on unobserved household- and energy-specific terms. This model is preferred over the standard pooled MNL, which ignores the unobserved household and energy type-specific effects (Fentie et al., 2023).

The assumption behind random effects is that the unobserved household effect is independent of the explanatory variables. When no omitted variables are present, random effects estimation is more efficient, unbiased, and consistent than fixed effects estimation. Although fixed effects estimation can yield consistent results, it is inefficient when time-invariant unobserved factors are correlated with the explanatory variables (Fentie et al., 2023).

An MNL form is used to express the probability of household i selecting an energy source at time t conditional on the control variables and unobserved household heterogeneity, which can be expressed as follows:

$$Pr(j, t/O_{it}, X_{it}, u_{i1}, u_{i2}) = \frac{exp(o'_{it}\gamma_j + x'_{it}\beta_j + u_{ij})}{\sum_{c=0}^{2}(o_{it}\gamma_c + x_{it}\beta_c + u_{ic})}, \qquad (4.3)$$

where $c=0$ is the base category for energy type, observable sociodemographic characteristics, power outages, and household-specific factors determine the probability that a household will select a particular type of energy. Furthermore, the distribution of the unobserved heterogeneity must be integrated because decision probabilities rely on unobserved heterogeneity effects. The MNL model with random intercepts has the following sample likelihood[10]:

$$L = \prod_{i=1}^{N} \int_{\infty}^{\infty} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{exp(o'_{it}\gamma_j + x'_{it}\beta_j + u_{ij}}{\sum_{c=1}^{3}(o_{it}\gamma_c + x_{it}\beta_c + u_{ic})} \right)^{\text{dijt}} f(\alpha) d\alpha, \qquad (4.4)$$

[10] The Random-Effects Multinomial Logit (RE-MNL) model was estimated using **Stata 18**, employing the xtmlogit command.

where d_{ijt}=1 if household *i* chooses energy source *j* at time *t*; otherwise, it equals 0. The base category's coefficients and the unobserved heterogeneity term are set at 0 for model identification. Unclean energy sources are the base category in our case. The unobserved heterogeneity α is assumed to be identically and independently distributed. Furthermore, the unobserved heterogeneity is unaffected by the explanatory variables, which are considered in the specification of any random effects model.

The standard MNL model operates under the independence of irrelevant alternatives (IIA) assumption, which means that the relative odds of choosing between two alternatives remain unaffected by the presence or absence of other options. While simplifying the estimation, this assumption fails to capture the complexities of household energy choices. In particular, the MNL model ignores household heterogeneity and assumes that decisions are independent across alternatives and over time. In this framework, the choice of one energy source does not influence the probability of selecting another, and household energy choices in one period are assumed to have no effect on future choices (Alem et al., 2016).

Nevertheless, energy choices are interrelated. For example, adopting solar panels could reduce a household's reliance on generators or grid electricity. In addition, past experiences with outages and dissatisfaction with specific energy sources shape future preferences. Changes in household characteristics, such as income and family size, alongside external factors, including technological advancements, policy shifts, and price changes, further complicate these choices. By adhering to the IIA assumption, the standard MNL model overlooks these critical interdependencies and the dynamic nature of household energy decision-making over time.

The panel MNL model with random effects addresses these limitations. In this model, u_{ij} represents the choice probabilities for a household's repeated decisions, sharing the same time-invariant unobserved heterogeneity. The household-specific effects function as a random variable. This causes the residuals for the same household within choices to correlate but maintains their independence within households. By incorporating random effects, the model allows for time-invariant unobserved heterogeneity, capturing the correlation between repeated choices made by the same household. This leads to more accurate and reliable estimates of the factors influencing household energy choices.

While the Random Effects Multinomial Logit (RE-MNL) model offers clear advantages for analyzing panel data, it is important to acknowledge its underlying assumptions and limitations.

A primary assumption is that the unobserved household-specific random effects are uncorrelated with the observed explanatory variables included in the model. In practical terms, this means that there are no omitted, time-invariant factors that simultaneously influence both a household's energy choice and the covariates, such as income or the frequency of power outages. This is a strong assumption and may not fully hold in real-world settings. For instance, a household's income might be correlated with its underlying, unobserved propensity to adopt solar technology—wealthier households may have greater access to information, stronger environmental preferences, or other latent traits that increase the likelihood of clean energy adoption. If such correlations are present, the RE-MNL estimates of the effects of observed predictors may be biased.

Despite this limitation, the RE-MNL model was chosen as a practical and robust compromise. Estimating a fixed-effects multinomial logit (or conditional logit) model in panel data with multiple choice categories is computationally demanding and often infeasible, particularly in datasets involving a large number of alternatives and repeated observations per unit. The RE-MNL framework allows for effective use of the panel structure while capturing a substantial degree of unobserved heterogeneity across households.

Nonetheless, the model still relies on the Independence of Irrelevant Alternatives (IIA) assumption, which states that the relative odds of choosing one alternative over another are unaffected by the presence or characteristics of additional alternatives. While the RE-MNL approach helps to mitigate unobserved heterogeneity, it does not fully relax the IIA assumption. Given the technical complexity of testing IIA in random-effects multinomial logit models with panel data, formal testing was not conducted in this study. As such, we acknowledge that if the IIA assumption is violated, the consistency of the RE-MNL estimates may be affected. These limitations should be taken into account when interpreting the model results, although the chosen approach remains a reasonable and empirically tractable strategy for the context and data structure of this study.

The transition probabilities were also estimated to examine the dynamics of household choices for energy sources. Transition probability estimation helps observe changes in household energy preferences over the study period.

4.5 Data and Sample Characteristics

This study uses data from Stats SA GHS, which has national coverage, to analyze household energy choices for lighting and the primary power source. GHS employs a robust sampling strategy to ensure representative data collection across the country's diverse demographics. Since its inception in 2002, the GHS has provided annual insights into the living conditions of South African households, particularly emphasizing energy choices, health, and other socioeconomic factors.

GHS uses a stratified two-stage sampling design to enhance representativeness and reduce sampling bias. In the first stage, PSUs are selected using probability proportional to size sampling. This method ensures that larger PSUs are more likely to be chosen, reflecting their significant contribution to the overall population. Subsequently, systematic sampling is employed to select dwelling units (DUs) within each PSU, allowing for a diverse representation of living conditions and energy choices. This structured approach helps obtain a sample that accurately reflects the various socioeconomic contexts in South Africa.

Since 2015, GHS has utilized a master sample frame developed in 2013. This frame standardizes sampling procedures across all household-based surveys conducted by Stats SA. Detailed data from the 2011 census provide a robust and current sampling foundation that reflects the dynamics of South African households.

Data were collected through face-to-face interviews, thus contributing high-quality data. From 2016 to 2018, Stats SA collected information from 21,228 DUs in 2016, 21,225 in 2017, and 20,908 in 2018. Notably, approximately two-thirds of these DUs remained in the sample for the entire analysis period, facilitating the construction of a balanced panel dataset through unique identifiers assigned to each DU. This longitudinal data aspect is crucial for understanding trends in energy choices over time.

This study focuses on households in formal dwellings with legal connections to the electricity grid, excluding informal dwellings. This deliberate focus allows for a more precise analysis of energy choices within a context in which households can access the established energy infrastructure. Furthermore, cases with missing data were removed from the final analysis to enhance the robustness of the findings. After cleaning the data, a panel dataset comprising 42,559 observations was obtained.

Two survey questions were used to analyze energy choices. The first question ("What is the main power source?") helps determine the adoption of PV systems. We categorized the responses according to their position on the energy ladder as follows: 0 for power from other less sustainable sources (e.g., generators), 1 for an in-house electric meter, and 2 for solar PV systems. The second question ("What is the main energy source for lighting?") informs our understanding of lighting fuel choices. Responses were classified as follows: 0, dirty fuels; 1, generators; 2, electricity; and 3, solar energy. This classification aligns with the energy ladder theory, which has been applied in previous studies (Fentie et al., 2023; Lay et al., 2013).

A dummy variable was created to measure blackouts based on responses to the question, "Did power interruptions last for more than 12 hours?" Households that reported experiencing such interruptions at least once were coded as 1, whereas those that did not were coded as 0. This question targeted households encountering power outages without prior notification and not due to nonpayment. The dummy variable is necessary because of the low frequency of households reporting interruptions more than twice.

The duration of these power interruptions was used as a proxy for blackouts because it more accurately reflects the impact of prolonged outages. A protracted power outage is defined as an interruption in electrical service for an extended period, typically exceeding 12 consecutive hours. This duration is significant because it can disrupt daily activities, impact household routines, and influence energy choices and behaviors. Prolonged outages can create significant inconveniences and challenges for households, such as difficulties in accessing essential services, maintaining food storage, and using appliances that require a consistent power supply.

Household income is crucial for determining energy choices and is central to this analysis. The energy ladder hypothesis proposes that households transition from traditional, polluting fuels to cleaner options (e.g., electricity and solar power) as their incomes rise (Lay et al., 2013; Fentie et al., 2023; Best, 2023). This transition is often accompanied by increased environmental awareness, particularly among higher-income households who may prioritize sustainability because of financial capacity and climate change concerns (Rahut et al., 2018). Therefore, economic factors and evolving values likely drive the relationship between income and energy choices.

Furthermore, this study considers the characteristics of the household head, recognizing their significant influence on energy-related decisions. Age, gender, marital status, and education can shape preferences for different races and consumption patterns. For example, age can be a proxy for generational differences in attitudes toward new energy sources and technologies. Older individuals may have ingrained habits and preferences for traditional energy sources, whereas younger generations might be more receptive to newer, cleaner technologies (e.g., solar).

Gender and marital status can also play significant roles in energy choices within households. For example, female-headed households may prefer clean and sustainable energy sources to reduce reliance on hazardous fuels, such as kerosene or firewood, which pose health and safety risks. Additionally, adopting solar energy can save significant time by eliminating the need to collect firewood or procure kerosene—tasks that often disproportionately fall on women in numerous households.

Another crucial factor is education level. Higher education can enhance awareness and understanding of different energy options, including their environmental impacts. Education can provide individuals with the skills to evaluate the costs and benefits of different energy sources, enabling them to make informed decisions that align with their household's needs and values. By considering these individual characteristics, the analysis provides a more nuanced understanding of the factors influencing household energy choices.

Table 4.1 provides definitions of the variables used in this study and presents descriptive statistics. This table shows that electricity is the predominant energy source for lighting and the main source of supply in South African households. Approximately 8% of households experienced significant power interruptions lasting more than 12 hours. The average age of household heads is 51 years, with 47% of households headed by women and 36% comprising married individuals. In terms of education, 23% of household heads had primary education, whereas 66% completed high school or higher. The average household income is R 9,838.

Table 4.1: Descriptive statistics of key variables

Variable	**Description**	**Mean**	**SD**
Main power energy source	0: other sources, 1: electric meter, 2: solar PV	0.897	0.312
Lighting energy source	0: dirty fuel, 1: generator, 2: electricity, 3: solar source	1.908	0.412
Outages	If household reported outages ≥ 12 h—1: reported interruptions at least once, 0: otherwise	0.076	0.265
Age	Household head age in years	51.124	15.678
Female	Gender of household head—1: female, 0: otherwise	0.471	0.499
Married	Marital status of household head—1: married, 0: otherwise	0.357	0.479
Primary education	If the household head reported primary education—1: primary education, 0: otherwise	0.228	0.419
Senior education	If the household head reported secondary education and higher—1: senior education, 0: otherwise	0.657	0.474
HH income	Household income in rand	9,838.01	18,740.72

Table 4.2 provides summary statistics on household energy sources, broken down by whether households experienced power outages. A notable finding is the difference in the primary source of electricity. Households that did not experience outages were more likely to rely on in-house electric meters. In contrast, households that experienced outages showed a higher

dependence on electricity from other sources (i.e., generators). Approximately 33% of households with outages use electricity from generators or other sources, compared with only 9% of households without outages.

Table 4.2: Household energy sources by outage status

Variables	All samples	No outages (a)	Observations	Outages (b)	Observations	Mean difference (a-b)
Main source of power						
Other sources	0.105	0.087	39,307	0.325	3,252	−0.238***
Electric meter	0.891	0.911	39,307	0.663	3,252	0.248***
Solar PV	0.003	0.002	39,307	0.012	3,252	−0.010***
Main source of lighting						
Dirty fuel	0.038	0.040	39,307	0.022	3,252	0.018***
Generator	0.020	0.016	39,307	0.077	3,252	−0.061***
Electricity	0.936	0.940	39,307	0.889	3,252	0.051***
Solar	0.0053	0.005	39,307	0.012	3,252	−0.007***

Households experiencing power outages are significantly more likely to adopt PV systems. However, these systems only partially eliminate reliance on the grid. During periods of extended cloud cover or low sunlight, households still require grid electricity to maintain a stable power supply, particularly in areas with frequent or prolonged outages. Therefore, solar PV is a complementary solution that mitigates some challenges of load-shedding rather than a complete replacement for grid connectivity.

Electricity is the dominant source of lighting fuel for households without outages, covering approximately 94% of their lighting needs. Remarkably, households without outages rely more on unclean fuels (4%) compared to households with outages (2.2%). Conversely, the use of generators and solar sources for lighting was significantly higher among households that reported blackouts. These findings suggest that power outages drive households to seek alternative energy sources, with a notable shift towards generators and, to a lesser extent, solar energy, while reducing dependence on grid electricity. The lower use of unclean fuels among outage-affected households may indicate a preference for more reliable or cleaner backup options. However, the limited adoption of solar energy highlights potential barriers such as cost and accessibility.

4.6 Analysis and Results

Table 4.3 shows the results for the random effects MNL. The estimated coefficients for households' primary power sources are compared with electricity from other sources, which is the base category in this model. The results reveal a clear relationship between power outages and household energy choices. Extended power outages significantly reduce the likelihood of households relying on the electric grid as their primary power source. Conversely, more extended outages increase the probability of households adopting solar PV systems to meet their daily energy needs. When power outages exceed 12 hours, a notable shift from grid reliance to solar power is noted, demonstrating the growing importance of solar energy as a reliable alternative when grid electricity is unreliable.

The results show that socioeconomic factors play a significant role in household energy choices, alongside the impact of power outages. Older household heads, female-headed households, and married households prefer grid electricity and solar PV systems. The positive age coefficients for electric and solar meters indicate that older households are more likely to choose these options over other less sustainable clean sources, which may reflect their excellent financial stability or a stronger preference for reliable energy.

Female-headed households are significantly more likely to adopt electric meters and solar PV systems. These households might prioritize more reliable energy sources for different energy needs, such as cooking, childcare, and other domestic tasks. They may be more concerned about health and environmental impacts. Additionally, it could reflect the growing empowerment of women in decision-making roles, particularly in managing household resources. Female-headed households might allocate resources differently, prioritizing energy access over other expenses.

Table 4.3: Random effects analysis: Main power source selection

Variables	Electric meter	Solar PV
Base category: other sources		
Outages	−1.862***	1.946***
	(0.080)	(0.409)
Age	0.0439***	0.0460**
	(0.002)	(0.015)
Female	0.414***	1.308***
	(0.073)	(0.463)
Married	0.381***	1.339***
	(0.078)	(0.490)
Primary education	0.561***	−0.108
	(0.113)	(0.561)
Senior high education	1.110***	−0.565
	(0.116)	(0.618)
HH income	0.0000109***	0.0000204***
	(2.43e-06)	(5.04e-06)
Observations	42,559	42,559

*$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

Being married is positively associated with the likelihood of choosing both electric meters and solar PV compared with other energy sources. This finding can be attributed to the higher combined household income, which increases the financial capacity to invest in more reliable and sustainable energy solutions. In addition, married households may have different energy needs, particularly if they have larger families, which could drive the demand for stable and consistent energy sources. The increased energy requirements for family-related activities, such as cooking, heating, and childcare, might further explain their preference for dependable options, such as electric meters and solar PV systems.

Higher education is associated with greater use of grid electricity. However, education does not appear to significantly influence the adoption of solar PV systems, indicating that other factors besides awareness influence this choice.

Our findings on the effect of income empirically confirm the well-established Energy Ladder Hypothesis. This hypothesis posits that as household income increases, people tend to move up an "energy ladder" by adopting progressively cleaner, more efficient, and often more convenient energy sources. Our results show that when incomes rise, households are indeed more likely to choose electric meters and solar PV as their primary power sources. This is intuitively sensible: higher incomes provide the financial means to afford the connection fees for grid electricity, the cost of modern appliances like electric stoves, and the investment in cleaner alternatives such as solar PV systems. Beyond mere affordability, modern energy sources offer significant improvements in convenience, reliability, and overall quality of life, eliminating the laborious need for fuel collection and reducing indoor air pollution. For many, transitioning to electricity or solar PV also aligns with aspirations for a modern lifestyle, where improved living standards are often associated with access to advanced energy solutions. These findings are consistent with previous studies by Lay et al. (2013) and Best (2023), further demonstrating that household transitions to clean energy sources increase with rising income levels, cementing income's role as a primary driver in these energy shifts.

Table 4.4 presents the results of the random effects MNL model, examining households' main lighting fuel choices, with unclean fuels (e.g., kerosene or biomass) set as the reference category. The estimated coefficients allow for comparing the influence of different factors, such as exceptionally prolonged power outages, on household decisions about their primary lighting source. The results demonstrate that power outages significantly influence household lighting decisions. Households experiencing outages of more than 12 hours are more likely to use generators, solar power, or grid electricity for lighting rather than relying on unclean fuel sources.

This finding highlights the influence of energy insecurity on short-term adaptation and long-term energy choices. Numerous households rely on generators for lighting because they are immediately available during blackouts. However, the positive and significant solar energy and grid electricity results reveal a more complex scenario. Some households are shifting to cleaner and more reliable lighting solutions despite the challenges of unreliable grids. Households that remain connected to the grid prioritize electricity as their primary lighting source, indicating trust in the grid's potential reliability. In addition, more households are investing in solar technology, showing a growing preference for sustainable and independent energy sources. These findings illustrate the multifaceted nature of household energy decision-making, in which immediate needs, long-term goals, and perceptions of future reliability intersect.

Table 4.4: Random effects analysis: Lighting fuel selection

Variables	Generator	Electricity	Solar
Outages	2.207***	1.526***	1.552***
	0.237	0.197	0.351
Age	−0.0441***	0.0306***	0.0132
	0.007	0.004	0.011
Female	−0.506**	0.324***	0.622**
	0.018	0.123	0.315
Married	−0.0089	0.610***	0.780**
	0.203	0.136	0.333
Primary education	1.346***	0.687***	0.149
	0.307	0.160	0.402
Senior high education	2.418***	1.970***	0.145
	0.307	0.179	0.449
HH income	9.65e-06	0.0000343***	0.0000389***
	9.3e-06	6.45e-06	7.87e-06
Observations	42,559	42,559	42,559

*$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

The findings reveal a complex relationship between household characteristics and lighting fuel choices. The age of the household head has mixed effects on fuel selection. Older heads are less likely to rely on less sustainable clean sources, such as generators, and are more likely to choose grid electricity as their primary energy source. Accordingly, they prefer the perceived reliability and familiarity of grid power, despite the risk of outages. Although there is a slight indication that older households might be more inclined toward solar energy, this trend is not statistically significant; hence, age is not a major factor in solar adoption.

Gender significantly influences household lighting fuel choices: female-headed households demonstrate a higher probability of transitioning to clean and renewable energy sources. This finding aligns with previous studies (Ngoma et al., 2018; Baek et al., 2020). In addition, marital status influences fuel choices: married households are more likely to transition to electricity and solar energy for lighting. The education level of the household head is positively associated with a transition toward electricity use; however, it has an insignificant impact on solar adoption. These findings are consistent with previous studies (Lay et al., 2013; Khundi-Mkomba et al., 2020), which noted that better-educated households choose cleaner fuels, although there is insignificant statistical evidence for education influencing the probability of using solar for lighting.

Income emerges as a crucial factor, positively and significantly affecting the probability of choosing clean and modern fuels. An increase in household income correlates with a higher likelihood of selecting electricity and solar energy for lighting, confirming the energy ladder hypothesis that higher income significantly affects households' transition to modern fuels. These results align with previous findings (Lay et al., 2013; Baek et al., 2020; Fentie et al., 2023), which indicate that households with higher incomes and wealth are more likely to opt for clean energy sources.

Table 4.5: Probability of change in primary energy sources

Household transition probabilities (%)			
Main power sources	**Power sources**		
	Other sources	Electric meter	Solar PV
Other sources	64.08	35	0.92
Electric meter	4.81	95.16	0.02
Solar PV	39.24	15.19	45.57

Table 4.5 presents the transition probabilities to renewable energy sources, focusing on household shifts in primary power sources according to the energy ladder framework. The rows represent households' initial energy sources, and the columns indicate their future energy choices. For households relying on other sources, such as generators, 64% are likely to continue using this source in the following year. In comparison, 35% may transition to grid electricity (electric meters), and only 1% may transition to solar PV systems. Households already using grid electricity demonstrate a strong tendency to remain with this option (95% probability), with a small fraction (5%) potentially reverting to less clean alternatives and a minor proportion (0.02%) adopting solar PV systems.

Approximately 46% of households that utilize solar energy will continue to use this source. In contrast, 39% may revert to less clean sources, and 15% may adopt electric meters. The significant likelihood of households switching back to less clean energy sources is likely driven by the high costs associated with solar PV systems, especially as long-lasting power outages in South Africa demand higher-capacity solar setups. Without government subsidies to offset these costs, households may find it more financially viable to switch to cheaper alternatives despite the long-term benefits of solar energy.

Table 4.6: Changes in household lighting fuel choices

Household transition probabilities (%)				
Lighting sources	**Lighting fuel sources**			
	Dirty fuels	Generators	Electricity	Solar
Dirty fuels	59.28	4.33	32.85	3.53
Generators	5.93	61.94	31.96	0.17
Electricity	1.42	1.87	96.65	0.07
Solar	29.84	1.57	18.85	49.74

Table 4.6 reports households' transition probabilities to different lighting sources. Among households using unclean fuels as their primary lighting source, 59% are likely to continue using them the following year. However, approximately 4% of these households are expected

to switch to generators, 33% to electricity, and 4% to solar power. Households currently using generators for lighting have a 6% probability of reverting to unclean fuels, a 32% probability of adopting electricity, and a 0.17% probability of transitioning to solar power.

For households using electricity as their primary lighting source, 1% are expected to revert to unclean fuels, 2% to generators, and 0.07% to solar power. Approximately 50% of households that use solar energy as their primary lighting source will continue to do so. However, a significant percentage (19%) may switch to electricity. In comparison, 30% could return to unclean fuel and 2% to generators.

Households' tendency to revert to less sustainable energy sources, as observed in lighting and primary power sources, emphasizes the financial barriers to adopting cleaner alternatives. High grid electricity and solar technology costs, combined with a lack of government support, push households toward cheaper but more polluting options. In the absence of policy interventions to make solar energy more affordable, households may continue to rely on cheaper, unclean fuels, which could negatively impact public health and environmental well-being.

Table 4.7: Probability of change in primary energy sources by gender

		Household transition probabilities (%)		
Variables	**Main power sources**	**Power sources**		
		Other sources	Electric meter	Solar PV
Female-headed households	Other sources	47.37	50.47	2.16
	Electric meter	3.16	96.82	0.02
	Solar PV	40.00	12.50	47.50
Male-headed households	Other sources	55.17	44.10	0.73
	Electric meter	4.32	95.64	0.04
	Solar PV	37.50	8.33	54.17

To explore patterns of energy transition over time by gender, we present descriptive statistics on household movement between primary power sources using transition probability matrices[11]. Table 4.7 shows the transition probabilities of households moving between different primary power sources—other sources, electric meters, and solar PV systems—disaggregated by household head gender. For female-headed households, 50% who relied on other sources were likely to transition to electric meters, 47% remained with other sources, and 2% adopted solar PV systems. Among those using electric meters, the majority (97%) continued using electric meters, 3% were likely to revert to other sources, and only 0.02% transitioned to solar PV systems. Households using solar PV systems showed a notable dynamic: 47.5% were likely to retain solar PV systems, 12.5% switched to electric meters, and 40% reverted to other sources.

A similar pattern emerges for male-headed households, but with some variations. Among those using other sources, 44% are likely to transition to electric meters, 55% stay with other sources, and only 0.73% adopt solar PV systems. Households relying on electric meters showed high stability, with approximately 96% continuing their use, 4% likely switching to other sources, and only 0.04% moving to solar PV systems. Solar PV users in male-headed households exhibited excellent retention (54.17%). However, around 38% may switch to other sources, and 8% may transition to electric meters. Accordingly, although solar PV retention is higher in male-headed households, female-headed households show slightly more transitions to electric meters and other sources, indicating potential gendered differences in energy decisions and energy use stability.

Table 4.8 shows the transition probabilities of households shifting between different lighting fuel sources—unclean fuel, generators, electricity, and solar sources—disaggregated by the gender of the household head. 52% of female-headed households using unclean fuels are likely to continue using this source. However, approximately 43% transition to electricity, 4% adopt solar systems, and 0.85% switch to generators. Among those relying on generators, 50% may continue using them, 48% may transition to electricity, around 2% may revert to unclean fuels,

[11] Descriptive transition probability tables generated using the xttrans command in Stata 18 illustrate observed shifts in energy choices over time but do not provide standard errors or confidence intervals for statistical inference. Therefore, direct comparisons of percentages between groups based on these tables should be interpreted with caution, as observed differences may not be statistically significant. For rigorous hypothesis testing and to assess gender-specific effects, our primary analysis relies on Random-Effects Multinomial Logit models estimated with interaction terms.

and only 0.82% may adopt solar systems. Electricity users exhibited high stability, with 98% retaining it. However, a small percentage may transition to unclean fuels (1.10%), generators (0.63%), or solar systems (0.05%). Solar users were more dynamic: approximately 57% are likely to continue using this source, 28% may revert to unclean fuels, 14% transition to electricity, and 1% may adopt generators.

Table 4.8: Changes in household lighting fuel choices by gender

		Household transition probabilities (%)			
Variables	**Lighting sources**	**Lighting fuel sources**			
Female-headed households		Dirty fuels	Generators	Electricity	Solar
	Dirty fuels	52.34	0.85	42.55	4.26
	Generators	1.64	50.00	47.54	0.82
	Electricity	1.10	0.63	98.22	0.05
	Solar	27.78	1.11	14.44	56.67
Male-headed households					
	Dirty fuels	53.62	1.96	42.07	2.35
	Generators	3.36	62.75	33.89	0.00
	Electricity	1.10	1.20	97.62	0.08
	Solar	11.76	1.96	27.45	58.82

Furthermore, approximately 54% of male-headed households using dirty fuels are likely to continue using them. However, 42% may transition to electricity, 2% to solar systems, and 2% to generators. Stability is higher among generator users, with 63% expected to retain generators, 34% likely to switch to electricity, 3% potentially reverting to dirty fuels, and none expected to adopt solar systems. Electricity users demonstrated a high retention rate of 98%, with a small likelihood of transitioning to dirty fuels (1.10%), generators (1.20%), and solar systems (0.08%). Solar users exhibited slightly lower retention (58.82%), with 27% transitioning to electricity, 12% reverting to dirty fuels, and 1.96% adopting generators. Overall, female-headed households display more dynamics in changing fuel sources, potentially reflecting differences in energy preferences or constraints.

4.7 Further Exploration

An analysis was conducted based on gender to explore the impact of power outages on different populations. By analyzing data separated by gender, we aimed to identify potential differences in energy choices and behaviors during power disruptions.

Table 4.9: Random effects analysis: Main power source selection by gender

Variables	**Electric meter**	**Solar PV**
Base category: other sources		
Outages	−1.937***	2.022***
	(0.131)	(0.550)
Other control variables	Yes	Yes
Observations	20,078	20,078

*$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

As shown in Table 4.9, power outages significantly influence female-headed households' choice of primary energy sources. The negative coefficient for electric meters highlights that frequent outages reduce reliance on grid electricity, likely due to its unreliability. In contrast, the positive and significant coefficient for solar PV adoption indicates that female-headed households increasingly view solar energy as a viable alternative during power outages. This preference for solar PV may stem from its practical benefits in daily life, offering self-sufficiency crucial for managing essential tasks like cooking and childcare, and reducing the stress of power outages for women balancing multiple household responsibilities.

Table 4.10: Random effects analysis: Lighting fuel choices by gender

Variables	**Generator**	**Electricity**	**Solar**
Outages	2.821***	1.639***	1.484**
	(0.391)	(0.308)	(0.504)
Other control variables	Yes	Yes	Yes
Observations	20,078	20,078	20,078

*$P < 0.10$, **$P < 0.05$, ***$P < 0.01$.

Table 4.10 presents the results for lighting fuel choices in female-headed households. These results reveal that power outages significantly influence the adoption of generators, grid electricity, and solar energy, each reflecting a distinct household strategy for coping with an unreliable electricity supply. To examine whether the effect of power outages on household energy choices varies by gender, we estimated an extended random-effects multinomial logit (RE-MNL) model that included an interaction term between outages and the gender of the household head (female), along with standard control variables. Although descriptive patterns suggested some differences in magnitude between male- and female-headed households, the interaction term (c.outages#i.female) was not statistically significant across any energy source category (see appendix table A4.1 & table A4.2). This suggests that, once we account for observed household characteristics and unobserved time-invariant heterogeneity, the influence of outages on energy choices does not differ meaningfully by gender in this sample. While these findings do not provide formal evidence of gender-based heterogeneity in response to outages, they do not preclude the possibility of more nuanced gender dynamics. Future studies could leverage larger samples, more detailed intra-household decision-making data, or qualitative methods better to capture gendered energy transition pathways and decision processes.

4.8 Robustness Check

Further analyses were conducted using fixed-effect estimation to enhance the robustness of our findings and address potential biases associated with the random effects model. Although random effects models are efficient, they rely on the strong assumption of no correlation between unobserved household characteristics and independent variables. Conversely, fixed effect models control all time-invariant household factors, providing a more rigorous test of the relationships under study by leveraging within-household variation over time. This approach effectively mitigates potential omitted variable bias. By comparing results from both models, we assess the sensitivity of our findings to different assumptions, with consistent results across specifications, enhancing confidence in the robustness of our conclusions regarding the determinants of household energy choices in South Africa.

Notably, several observations can be excluded when using a fixed effects model with a short time panel. If a household experiences no change in key variables (e.g., income and fuel choice) over the 3 years, its data are not used in the estimation, as fixed effects models focus on within-household changes. These exclusions do not necessarily introduce bias unless the omitted households systematically differ from the included ones. Therefore, the fixed effects model remains focused on analyzing time-varying factors.

Table 4.11: Determinants of household energy source: Fixed effects

Variables	**Electric meter**	**Solar PV**
Outages	−0.906***	3.026***
	(0.083)	(0.805)
Age	0.0116***	0.0966***
	(0.004)	(0.043)
Female	−0.0019	1.187
	(0.102)	(0.957)
Married	−0.153	1.426
	(0.108)	(1.307)
Primary education	0.344**	−0.662
	(0.152)	(−0.62)
Senior education	0.267	(1.074)
	(0.160)	(−0.93)
HH income	0.00000382***	0.0000157***

	(2.25e-06)	(7.65e-06)
Observation	5,920	5,920

*$P < 0.10$, **$P < 0.05$, ***$P < 0.01$

According to the fixed effects model (Table 4.11), significant power outages strongly influence the electricity source choices of South African households. The results are broadly consistent with the findings of the random effects model, emphasizing the robustness and reliability of the observed relationships. In particular, the negative coefficient for "Outages" in the electric meter model and the positive and significant coefficient for solar PV indicate that prolonged outages drive households away from grid electricity and toward solar power as an alternative. These statistically significant effects highlight the influence of power outages on household energy decisions.

Table 4.12: Determinants of household lighting fuel: Fixed effects

Variables	**Generator**	**Electricity**	Solar
Outages	0.961***	1.357***	1.095**
	(0.219)	(0.181)	(0.393)
Age	0.007	0.010	0.023
	(0.011)	(0.007)	(0.024)
Female	−0.205	−0.212	−0.677
	(0.264)	(0.187)	(0.538)
Married	−0.235	−0.142	0.0146
	(0.285)	(0.213)	(0.584)
Primary education	0.313	0.19	−0.0694
	(0.444)	(0.208)	(0.578)
Senior high education	0.369	0.293	−0.0779

	(0.455)	(0.246)	(0.705)
HH income	0.0000142	0.0000171**	0.0000246**
	(0.000)	(8.45e-06)	(0.000)
Observations	**3,282**	**3,282**	**3,282**

*P < 0.10, **P < 0.05, ***P < 0.01

Table 4.12 presents the fixed effect estimation results, highlighting the relationship between household lighting fuel choices and power outages. These results offer valuable insights that align with the findings of the random effects model. The statistically significant positive coefficients for the "Outages" variable across all fuel types (generator, electricity, and solar) indicate the critical role of power disruptions in encouraging households to diversify their lighting energy sources. Generators remain the most used during outages. However, although smaller, the positive coefficient for solar power indicates its growing importance as a backup energy source. This finding reflects a broader shift toward clean, renewable energy. The consistency of the results between the fixed and random effects models enhances the robustness and generalizability of the study conclusions, providing strong evidence of the impact of power outages on household energy choices.

Table 4.13: Conditional Fixed-Effects Logistic Regression

Variables	**Solar PV**	**Solar Lighting**
Outages	3.222***	.263
	(0 .804)	(0.359)
Control variables	Yes	Yes
Observations	**194**	**309**

*P < 0.10, **P < 0.05, ***P < 0.01

To further validate our findings on the drivers of energy transitions, we conducted a Conditional Fixed-Effects Logistic Regression for two key binary outcomes: adoption of solar PV as a primary power source and adoption of solar for lighting (results presented in Table

4.13). These models control for all unobserved time-invariant household characteristics by focusing on within-household changes. For solar PV as a primary power source, the fixed-effects model largely corroborated our primary results: power outages, age, and net income significantly increased the likelihood of a household switching to solar PV. However, for solar PV explicitly used for lighting, the fixed-effects model did not yield statistically significant results for any of the included predictors. This suggests that while outages and income robustly drive the adoption of solar as a primary energy solution, the decision to switch to solar for lighting may be influenced by different, perhaps more nuanced or unobserved, within-household dynamics not captured by our time-varying covariates in this stringent fixed-effects specification. This comparative robustness check therefore highlights distinct drivers and complexities across different energy end-uses within the household.

4.9 Conclusion and Policy Insights

South Africa has grappled with an enduring energy crisis, manifested in persistent and often prolonged power outages. This unreliable electricity supply, stemming from years of underinvestment and mismanagement within Eskom, has disrupted the daily lives of households nationwide. Faced with frequent blackouts that can last for 12 hours, South African households have increasingly shifted to alternative energy sources, particularly for essential needs such as lighting. This study provides novel insights into the determinants of household solar PV adoption and lighting fuel choices in South Africa, focusing on the impact of extended power outages.

Employing a random effects MNL model with data from Stats SA GHS (2016–2018), this study finds strong evidence that power outages significantly influence household energy choices. Extended outages increase the probability of households adopting solar energy and decrease their reliance on grid electricity. This shift toward solar energy is supported by the income level, which is consistent with the energy ladder hypothesis. In addition, extended power outages influence households' lighting fuel choices, with a positive and significant probability of shifting to solar lighting during outages. Gender also impacts energy choices, with female-headed households more likely to adopt clean, sustainable options (e.g., solar energy) than male-headed households. Consequently, women, who often manage household resilience during power disruptions, are more inclined to prioritize reliable and clean energy sources. These findings underscore the significant impact of gender on energy decisions and highlight the critical role of energy security in driving the adoption of renewable energy technologies in South Africa. This study also observed a significant probability of households transitioning to renewable energy sources for their primary power source and lighting. However, approximately one-third of households using solar energy will likely revert to less sustainable options. This shift can be attributed to the high cost of solar technology in South Africa. The following policy recommendations are proposed based on the findings to address energy insecurity and support sustainable energy transition in South Africa:

1. The government should implement financial incentives to reduce initial investment costs for households adopting solar PV systems, including subsidies, tax breaks, and low-interest loans for renewable energy investments.

2. The solar infrastructure should be strengthened by investing in comprehensive support services and maintenance networks to ensure the long-term sustainability of solar energy adoption and help households maximize the benefits of their investments. Addressing the fundamental causes of power outages through infrastructure upgrades and improved management of the power sector is also crucial for enhancing overall energy supply reliability.

3. To increase public awareness and acceptance of renewable energy, we recommend launching educational campaigns highlighting solar energy's benefits and informing households about available financial support options. These campaigns should target diverse demographic groups and address common misconceptions about renewable energy.

5. A solid monitoring system and alignment of renewable energy goals with national plans and global commitments ensure effective policies and support broader development objectives.

Although this study provides new evidence on the effect of power outages on energy transition when renewable energy options are available, our empirical analysis has several limitations. Limited data on solar adoption restricted the study of regional differences, emphasizing the need for more detailed data collection at the regional level. In addition, the lack of energy price data prevented a comprehensive examination of the economic factors influencing household energy decisions.

Future studies should focus on several key areas to better understand and promote renewable energy adoption. First, a detailed analysis of energy costs, including collaboration with energy providers, is required to assess their impact on household choices. Second, an investigation of regional disparities in energy adoption can provide nuanced, area-specific policy recommendations. Third, cross-country comparisons can offer valuable insights into best practices and innovative solutions for the adoption of renewable energy in diverse contexts. Finally, longitudinal studies that track households over time can reveal long-term trends and assess the sustainability of renewable energy adoption.

Chapter 5 consolidates the main findings from the three empirical studies: fuel stacking and health, power outages and well-being, and solar adoption patterns. This chapter examines policy implications for fostering an equitable energy transition in South Africa and proposes directions for future research.

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Appendix II: The Interaction of Female Household Headship and Power Outages

Table A4.1: RE-MNL Results for Main Power Source

VARIABLES	(1) meter	(3) solar	(4) /
outages	-1.971***	1.880***	
	(0.107)	(0.555)	
1.female	0.379***	1.263**	
	(0.0767)	(0.532)	
1.female#c.outages	0.251	0.133	
	(0.160)	(0.708)	
Age	0.0439***	0.0460***	
	(0.00276)	(0.0154)	
married	0.382***	1.334***	
	(0.0783)	(0.491)	
primary_edu	0.561***	-0.111	
	(0.114)	(0.562)	
senior_highedu	1.112***	-0.565	
	(0.117)	(0.619)	
netincome	1.09e-05***	2.04e-05***	
	(2.43e-06)	(5.41e-06)	
var(u1)			12.61***
			(0.985)
var(u2)			22.64***
			(6.061)
cov(u1,u2)			-11.67***
			(2.050)
Constant	1.361***	-17.09***	
	(0.225)	(2.185)	
Observations	42,559	42,559	42,559
Number of unid	14,519	14,519	14,519

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.2: RE-MNL Results for lighting fuel choices

VARIABLES	(2) generator	(3) elc	(4) solar	(5) /
outages	2.033***	1.443***	1.890***	
	(0.314)	(0.268)	(0.502)	
1.female	-0.565***	0.315**	0.709**	
	(0.198)	(0.125)	(0.327)	
1.female#c.outages	0.432	0.182	-0.641	
	(0.478)	(0.390)	(0.705)	
Age	-0.0440***	0.0306***	0.0127	
	(0.00736)	(0.00446)	(0.0112)	
married	-0.0118	0.610***	0.783**	
	(0.204)	(0.137)	(0.334)	
primary_edu	1.355***	0.689***	0.136	
	(0.371)	(0.160)	(0.403)	
senior_highedu	2.423***	1.971***	0.136	
	(0.371)	(0.180)	(0.450)	
netincome	9.40e-06	3.43e-05***	3.89e-05***	
	(9.04e-06)	(6.45e-06)	(7.89e-06)	
var(u1)				31.74***
				(3.532)
var(u2)				27.24***
				(2.029)
var(u3)				17.59***
				(4.108)
cov(u1,u2)				21.39***
				(2.026)
cov(u1,u3)				-9.399***
				(3.081)
cov(u2,u3)				-14.81***
				(2.851)
Constant	0.459	5.659***	-12.04***	
	(0.572)	(0.431)	(1.452)	
Observations	42,559	42,559	42,559	42,559
Number of unid	14,519	14,519	14,519	14,519

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 5: Synthesis, Conclusions, and Future Directions

5.1 Overview

This dissertation analyzed the energy shift in South Africa through three interrelated studies that offer essential insights into household energy selection, health effects, and well-being results. This report emerges at a pivotal moment with South Africa confronting unparalleled problems in its energy sector, marked by recurrent power outages, escalating electricity bills, and enduring energy poverty despite elevated electrification rates. These issues arise among global climate change demands and the necessity for sustainable development.

Three essential questions about household energy transition were discussed. First, how does fuel stacking—the concurrent use of different fuel types—impact household health outcomes about varying housing quality? Second, what are the concrete implications of inconsistent electricity supply on household welfare, and how do these effects differ across geographic and socioeconomic contexts? Third, what factors facilitate or hinder family adoption of PV systems, and how do gender dynamics influence these decisions?

Rigorous empirical analysis was conducted using advanced methodologies, such as DML and panel data analysis, to generate new insights into the complex relationships among energy availability, health, and well-being. These findings have significant implications for the academic understanding of energy transition and the development of practical policies in developing countries.

5.2 Principal Discoveries

This study identified notable patterns that contest traditional beliefs about energy transition and offer new insights into their effects on household well-being.

Examination of fuel stacking and health effects provided unexpected findings that challenge conventional notions of energy transition. Households employing fuel stacking exhibited 3% poorer health outcomes than those relying only on clean or unclean fuels. This unexpected finding underscores the vital role that home quality plays in influencing health outcomes. Residences with insufficient ventilation and substandard construction materials have markedly elevated rates of respiratory ailments, particularly among at-risk groups. The impact is particularly significant for elderly individuals and children, with respiratory problems increasing by approximately 4.1% in inadequately ventilated residences that use various fuel sources.

The analysis of power outages demonstrated considerable effects on SWB that differed markedly across regional and demographic factors. Frequent disruptions diminish self-reported satisfaction by approximately 10%, with urban areas exhibiting a 4.6% larger reduction than rural regions. This urban–rural discrepancy illustrates variations in household resilience strategies and the availability of alternative energy sources. Several critical mechanisms by which outages influence well-being were identified, such as disrupted cooking routines (affecting 37% of households), compromised food preservation (reported by 42% of impacted households), and interrupted income-generating activities (affecting 28% of urban households).

The analysis of solar adoption trends revealed intricate processes in family decision-making on renewable energy. Prolonged power outages increased the likelihood of households acquiring PV systems by 1.9%, indicating that an unpredictable grid supply incentivizes the pursuit of alternative energy sources. The sustainability of these transitions is questionable, as approximately one-third of solar adopters switch to nonrenewable energy sources because of financial constraints and maintenance difficulties.

These findings are interrelated and mutually supportive. The health consequences of fuel stacking and inconsistent energy supplies constrain household well-being. Likewise, the obstacles to sustainable solar adoption result in several homes being ensnared in cycles of fuel stacking despite their aspirations to shift to greener energy sources. These patterns collectively reflect the complex challenges South Africa encounters in its energy transition. These issues necessitate cohesive policy solutions that address several aspects of household energy consumption and accessibility.

5.3 Theoretical and Practical Contributions

This study advances academic understanding and practical strategies for energy transition in developing nations. The findings substantially contribute to the three main areas of scholarly debate while offering practical guidance for policy development.

Furthermore, this study enhances the energy justice theory by illustrating how partial transitions *via* fuel stacking can intensify rather than mitigate injustices. Conventional energy justice models have predominantly emphasized access and affordability. Nevertheless, our findings underscore the need to incorporate housing quality and gender dynamics as mediating variables in energy poverty. Ostensibly beneficial advancements, such as enhanced power availability, can yield unforeseen adverse effects if infrastructure quality and home circumstances are insufficiently managed.

The methodological changes in this study provide novel techniques for examining energy poverty. DML methodologies yield more accurate estimations of causal effects in intricate household decisions, mitigating endogeneity issues that have hindered prior research. Integrating this sophisticated econometric methodology with comprehensive household-level data facilitates a more nuanced understanding of the impact of energy decisions on health and well-being outcomes. Moreover, the panel analysis of power outage effects presents novel methods for estimating the societal costs of unpredictable electricity supply.

The findings address significant gaps in our understanding of changes in household energy use. The measurement of the health repercussions of fuel stacking offers definitive proof of how housing factors influence the effects of energy usage. Moreover, an examination of spatial discrepancies in outage effects reveals significant trends in urban–rural inequalities that other studies have overlooked. Recognizing gender disparities in solar adoption provides essential insights into household energy decision-making.

5.4 Policy Recommendations

The results highlight the need for comprehensive and integrated policy strategies across different levels of governance. Recommendations are organized by timeline and institutional level to facilitate practical implementation.

Immediate priority actions: The national government should implement a coordinated initiative that combines housing improvements with energy use. This initiative should include incentives for ventilation upgrades in residences that use various fuels, targeting at-risk households. Evidence indicates that such measures can reduce respiratory disease rates by approximately 4% and improve the effectiveness of sustainable energy initiatives.

Municipal governments must establish tailored support programs that recognize geographic disparities in energy requirements. Urban regions require concentrated efforts on backup power systems for critical services, whereas rural areas demand improved assistance for sustainable solar implementation. Programs must integrate gender-sensitive planning, acknowledging women's greater inclination toward sustainable energy adoption.

Medium-term initiatives: Financial institutions and governmental organizations should devise novel funding arrangements to facilitate the uptake of renewable energy. These arrangements may include pay-as-you-go solar systems and low-interest loans tailored for female-headed households, which are more likely to sustain the clean energy transition. Evidence indicates that minimizing initial expenses while offering continuous support may reduce the reversion rate to unclean fuels by nearly 30%.

Energy utilities must implement specific infrastructure improvements based on documented well-being effects. Priority should be given to locations showing the most significant decline in happiness due to outages, primarily urban areas where the negative impacts are most apparent. These efforts should be complemented by optimized maintenance schedules and enhanced grid resilience.

Prolonged structural modifications: A thorough overhaul of energy governance frameworks is necessary to enhance the coordination of national and local actions, entailing the formulation of explicit frameworks for the integration of renewable energy, the optimization of licensing procedures for residential solar installations, and the establishment of systems for knowledge exchange across municipalities.

The government should also develop a housing standard that addresses specific consumption trends and indoor air quality. This standard should encompass minimum ventilation standards for residences that utilize various fuel types and incentives for energy-efficient architectural designs.

5.5 Limitations of the Study

This study provides valuable insights. However, several limitations deserve attention. The cross-sectional design of the health impact analysis limits our ability to track the long-term effects of fuel usage patterns. Although the DML method reduces immediate causation issues, longitudinal data can more effectively clarify the cumulative impacts of energy choices.

Data limitations imposed additional constraints. The impossibility of directly quantifying IAP necessitated the use of proxy indicators based on fuel consumption patterns. Although earlier studies corroborate these proxies, actual measurements would yield more accurate pollution exposure assessments.

Although geographic coverage is nationally representative, it may fail to include all local energy access and consumption disparities. Specific isolated populations, mainly from rural regions, may have distinct issues that are not adequately represented in our sample. Furthermore, the swift progression of South Africa's energy crisis necessitates the revision of certain conclusions to align with contemporary circumstances.

Insufficient data on system expenses and maintenance needs have constrained the examination of solar adoption trends. This disparity hinders our ability to understand reversion trends for conventional fuels fully. Moreover, the duration of the research may not reflect recent changes in the pricing and accessibility of renewable energy technologies.

5.6 Conclusion

This thesis fundamentally reshapes our understanding of energy transitions in developing countries. We show that achieving sustainable energy access is far more intricate than simply replacing unclean fuels with modern ones. By analyzing fuel stacking, power reliability, and solar adoption among South African households, our research reveals that energy transitions are deeply tied to broader socioeconomic structures and geographic inequalities. These insights have significant implications for how energy policies are designed and implemented globally.

Our findings necessitate a shift in how we think about energy transitions. Simple, linear models, where households move directly from "unclean" to "clean" fuels, are inadequate for understanding and solving energy poverty. Instead, we show that a complex mix of factors, including housing quality, location, gender roles, and infrastructure reliability shapes household energy choices. This complexity is not just an academic point; it has real-world consequences for the millions of households still facing energy poverty despite many intervention efforts.

A surprising finding is that using a mix of fuels can lead to worse health outcomes than using only one type, whether clean or traditional. This challenges basic assumptions of current energy programs. It suggests that many well-intentioned interventions might accidentally worsen health by focusing only on fuel supply without considering the broader living conditions that influence how fuels are actually used. For policymakers, this means energy programs must be redesigned to include housing quality, ventilation, and cooking practices as central parts of energy access initiatives, not just as minor considerations.

Perhaps most importantly, this research expands our understanding of energy justice. It moves beyond simply measuring access to include the quality, reliability, and sustainability of energy services. The discovery that urban areas suffer greater well-being losses from power outages than rural areas challenges common beliefs about urban resilience. It also highlights how reliance on energy can create new vulnerabilities. This is critical for deciding where to invest in infrastructure and how to design strategies for resilience, especially as climate-related disruptions increase.

Our analysis of transitional probabilities in energy use offers key insights into both the adoption and discontinuation of solar energy. While some households successfully transition to solar, a striking pattern is the high rate of households reverting to other energy sources after initial adoption. This discontinuation—observed regardless of the household head's gender—signals that access to clean energy technology alone is not enough to secure lasting change. Instead, it calls for a fundamental rethinking of how energy programs are designed, funded, and supported over time, with greater emphasis on long-term affordability, reliability, and follow-up support.

We also find that female-headed households are more likely to adopt specific energy sources, as shown by the statistically significant main effect of gender. This underscores the role of household characteristics in shaping overall energy preferences. However, the absence of a significant interaction between gender and power outages suggests that unreliable electricity supply does not differentially affect energy decisions based on the gender of the household head. In other words, while gender influences general fuel choices, it does not appear to mediate how households respond to the specific challenge of power outages. Taken together, these findings point to the need for energy policies that go beyond technology provision to address structural and behavioural barriers to sustained clean energy use.

As the world urgently works to reduce greenhouse gas emissions while expanding energy access, this research offers key guidance for achieving both goals. Our findings suggest that climate policies focused only on technology will fail if they do not address the underlying social and economic factors that drive energy behaviours. This is particularly relevant for international climate finance, which must move beyond simple technology transfer to support complete transformations of energy systems.

The methodological innovations in this thesis, especially using double machine learning for household energy choices, provide new tools to understand and predict energy behaviours at a large scale. These methods can help policymakers identify which interventions are most likely to succeed in specific contexts, potentially making limited development resources more efficient and accelerating progress toward universal energy access.

Ultimately, this research demonstrates that achieving fair and sustainable energy transitions requires a fundamental rethinking of energy policy. Instead of viewing energy as a separate sector, we must recognize its deep connections with housing, health, gender equality, urban planning, and economic development. This interconnected perspective demands new forms of collaboration among government departments, development agencies, and research institutions.

Moving forward, we must go beyond technical solutions to embrace the social and political aspects of energy access. This means investing in local capabilities, supporting community-led energy initiatives, and designing policies that address the root causes of energy poverty, rather than just its symptoms. Only through such comprehensive approaches can we hope to achieve universal energy access and climate sustainability.

For South Africa and other developing countries, this research offers both a warning and an opportunity. The warning is that current approaches to energy transition are not enough to address the scale and complexity of energy poverty. The opportunity lies in embracing new ways of thinking about energy, recognizing its fundamental role in human development and environmental sustainability. By doing so, we can create energy systems that truly serve all members of society while protecting the planet for future generations.

5.7 Prospective Research

Future research should focus on several critical domains to overcome existing constraints and enhance our understanding of energy transition. Longitudinal research on the consequences of health and well-being over time will yield essential insights into the enduring implications of energy decisions. This should involve ongoing surveillance of indoor air quality in residences that utilize various fuel combinations.

The examination of household adaptation techniques during energy transition warrants significant focus. Research should investigate how households cultivate resilience to power interruptions and identify the characteristics that facilitate the effective management of clean energy systems. This research can encompass comprehensive case studies of households that effectively sustain solar adoption compared to those that revert to conventional fuels.

Another vital research domain is the function of informal energy markets in facilitating or obstructing transition. Future studies should investigate the impact of these marketplaces on home energy decisions and their potential influence on the facilitation or obstruction of clean energy uptake.