Evaluation of Household Carbon Footprints and Mitigation Strategies for Pakistan: A Consumption-Based Approach

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Dedication

Dedicated to my parents, whose enduring encouragement and prayers has remained my greatest source of strength.

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Abstract

Climate change threatens public health, the environment, agriculture, and the economy. The 13th Sustainable Development Goal (SDG) explicitly focuses on combating climate change and its impacts by reducing global carbon emissions. Households are the most significant economic agents responsible for most carbon emissions. This study aims to i) estimate the direct and indirect carbon footprints of household consumption and determinants in Pakistan, ii) analyze fuel and food consumption and substitution dynamics in Pakistan, iii) test the existence of EKC at the household level, and iv) propose mitigation strategies for households.This study used the 2015-16 and 2018-19 rounds of Pakistan's Household Integrated Economic Survey (HIES). The study used the (IPCC) reference method to estimate carbon emissions from cooking fuels, electricity and household consumption. The study used Heckman's two-stage selection model to evaluate the determinants of household carbon emissions. The study results revealed that households extensively used dung cake and firewood as cooking fuels in four provinces of Pakistan; therefore, these fuels mainly contribute to household carbon emissions. The analysis of food emissions shows that mutton has the most significant emissions among animal-based products, and rice emits the largest emissions among cereals. On the other hand, fruits and leafy veggies are among the lowest emitters. The Heckman model results demonstrated that household head characteristics, age, marital status, education, employment, and geographic distributions are highly associated with household energy consumption expenditures and their emissions. The study results indicate that household cooking emissions increase with the expenditure, but the results do not follow the inverted shape path of traditional EKC, which indicates that the economic condition of the household has not reached the position to adopt clean cooking fuels, which would lead to reduced emissions right now it is in the position of increased trajectory and not reached its inflexion point. The study results reveal that cooking fuels exhibit their price elasticity below unity, indicating a less than proportionate decrease in demand with an increase in prices. Additionaly, firewood and LPG, firewood and dungcake demonstrate substitution effects as evidenced by their respective cross-price elasticities. The study examines the environmental impact of food consumption patterns, highlighting high-emission foods like mutton, rice, and milk. We analyze how price elasticities influence consumer behavior, emphasizing the importance of promoting sustainable dietary choices. Integrating findings with existing literature, we propose policy implications to encourage eco-friendly food consumption, including targeting high-emission foods, understanding consumer responses to price changes, and implementing subsidies and carbon pricing to foster sustainable food systems. The study results reveal that cereal pulses and vegetables are close substitutes. The study contributes to understanding household cooking fuel, energy access and food consumption in Pakistan, shedding light on critical socio-economic factors that influence access disparities.The study concludes that policies should be designed by mainly focusing on improved technologies to make clean cooking stoves, investing in regional infrastructure, education and self-awareness programs to bridge the energy access gap and promoting clean and sustainable energy throughout Pakistan.

Keywords: household Carbon emissions, cooking fuel emissions, Heckman selection model, Pakistan

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Chapter 1

INTRODUCTION

1.1 Background

Humans grapple with two significant challenges, i.e., economic growth and environmental sustainability. These challenges are intertwined and involve complex connections. The environment has emerged as one of the most pressing issues facing both developed and developing economies today as environmental degradation raises concerns about global warming and climate change, which are primarily the result of greenhouse gas (GHG) emissions (Kasman & Duman, 2015; Uddin et al., 2017; Abbasi et al., 2022). In recent decades, environmental degradation caused by greenhouse gases (GHGs) has been an essential issue in the global environmental debate (Amin et al., 2022; Destek et al., 2022; Mitić et al., 2023; Ongan et al., 2023; Pata & Kartal, 2023; Simionescu et al., 2023).

Carbon dioxide emissions account for about 75% of GHG emissions and are a significant determinant of global warming and other climatic extremes (Yousaf et al., 2022; Abbas et al., 2023). The current IPCC 2021 climate scenarios show that global warming will exceed 1.5° C–2° C during the twenty-first century unless serious efforts are made to mitigate CO_2 and other GHG emissions. Moreover, the rising global temperature and extreme heatwaves are deteriorating the productivity of food crops and increasing global food insecurity (Destek & Aslan, 2020; Kousar et al., 2020; Okumus et al., 2021; Ameer et al., 2022; Ali et al., 2023; Bakry et al., 2023).

According to published research, an increase in economic growth of 2% may cause an increase in carbon emissions of 1% (Acheampong, 2018). Carbon emissions can indicate sustainable development since they measure resource quality and environmental impact. Carbon dioxide contributes a significant share (81 %) to greenhouse gas (GHG) emissions, followed by methane (10 %) and nitrous oxide (7 %) (EPA, 2020). Globally, 36.2 billion tons of CO_2 were emitted in 2017 (Le Quéré et al., 2018). The over-accumulation of these gases causes global warming and climate change.

Climate change poses global threats to public health, the environment, agriculture, and the growth of the economy (Patz et al., 2005; IPCC, 2007; Stern, 2007; IAASTD, 2008). Climate change affects the social and environmental determinants of health. According to the literature, climate change would increase income inequalities between and within countries by affecting the economic growth of many sectors, including agriculture, livestock, forestry, energy, tourism, and recreation industries. The impact of climate change on most of these sectors is highly uncertain (Schneider et al., 2007; Smith et al., 2001). The importance of climate change and its impacts is also highlighted in the sustainable development goals (SDGs). The 13th SDG focuses on combating climate change and its impacts by reducing global carbon emissions.

In line with the SDGs agenda, the United Nations urges adopting and developing green production technologies that can enhance overall productivity while reducing dependence on fossil fuels, a significant source of CO_2 emissions. Moreover, the environmental concentration of CO_2 emissions reached its highest level of 412.5 parts per million in 2020 (IEA, 2021). Emerging markets and developing countries are the major contributors to CO_2 emissions, accounting for more than two-thirds of the global emissions (Kartal et al., 2023; Ramzan et al., 2023). The most important contributor to CO_2 emissions is the consumption behavior of households, which is responsible for almost 72% of global greenhouse gas emissions (Dubois et al., 2019). Moreover, adopting green energy and technology at the household level can be the most effective policy intervention to achieve the sustainable economic growth plan proposed by the United Nations.

Such global environmental changes could significantly harm economic well-being and pose concerns about whether global society is on a sustainable path or is consuming too much by depleting vital natural resources (Arrow et al., 2004). These environmental changes raise essential social and economic aspects of sustainable development in addition to the environmental dimensions. Economic discipline plays a crucial role in achieving the challenge of sustainable growth.

Asia contributes the largest share of 19 billion tons per annum (53 %) to global carbon emissions. China is thethe world’s largest CO_2 emitter with 10 billion tons per annum, more than 50 % of Asia’s emissions. Emissions of greenhouse gases (GHG) from Pakistan are comparatively small, emitting only 199 million tons of CO_2 annually. It makes up only 1 % of

Asia's emissions, but in terms of the vulnerability index due to climate change, Pakistan is ranked in the 10th position from the top (Le Quéré et al., 2018).

Literature reveals that consumption behavior exerts an essential influence on GHG emissions. It is reported that a significant share of GHG emissions (more than 70 %) is based on household consumption (Minx et al., 2013). Therefore, before exploring solutions, it is essential to investigate the contribution of different consumption items (i.e., energy and food) to carbon emissions. It would help to understand the current carbon footprints of household consumption in Pakistan.

The sum of all carbon emissions induced by human activities is quantified as "carbon footprints" in the literature (Druckman & Jackson, 2009; Minx et al., 2013; Wiedenhofer et al., 2016). The origin of carbon footprints is a subset of the "ecological footprint" proposed by Wackernagel and Rees (1996). The carbon footprint measures the carbon dioxide emissions generated by economic activity (production and consumption) (Wiedmann & Minx, 2007). In other words, it is the total GHG emission caused directly and indirectly by an individual, organization, event, or product (Sulaimon, 2018).

Households, the most significant economic agents in any society, are responsible for most carbon footprints (Brizga et al., 2016; Druckman & Jackson, 2009; Kennedy et al., 2014). If a consumer's activity consumes energy such as gas, electricity, petroleum products, coal and biomass, it leads to carbon emissions and refers to direct influences (Bin & Dowlatabadi, 2005; Druckman & Jackson, 2009). If energy consumption and carbon emissions arise in the preparation of a product or service, for example, food, goods and services used by households, are called indirect influences (Pandey et., 2011; Bhoyar et al., 2014; Büchs & Schnepf, 2013b). GHG emissions vary from household to household and place to another, depending on people's lifestyles directly related to energy use habits, fuel and domestic transport. Consequently, estimating carbon footprints at a micro level is a first step towards a better understanding of household's impacts on national and global climate change (Amin et al., 2023).

Domestic energy consumption is used within households for space and water heating, cooking, lighting and electrical appliances (Roberts, 2008; Gough et al., 2011; Bhoyar et al., 2014). This study focuses on three primary household energy sources, i.e., electricity, cooking fuels, and fossil fuels in private transportation. Electricity consumption is distributed among the three main household activities, i.e., hygiene (washing machine, water heaters, irons and vacuum cleaners), eating (kettles, refrigerators, dishwashers, etc.) and leisure (TV sets, PCs, Laptop and mobile phones)(Rosin et al., 2010). In Asia, 351 million and in Pakistan, 52 million people have no access to electricity. The electrification rates are 91 % and 74 % in Asia and Pakistan, respectively (Irena, 2019).

Households have a limited choice of fuels, primarily due to availability, affordability, and accessibility. The traditional fuels used for cooking and heating are fuel wood, agricultural waste, and animal dung, while clean cooking fuels include biogas, Liquefied Petroleum Gas (LPG) and natural gas. In Asia, 44 % of the population needs clean cooking access. However, in Pakistan, 66 % population needs access to clean cooking sources (Irena, 2019). Burning fossil fuels (i.e., oil, coal and gas) is the energy source for transportation, accounting for 60-70 % (Smil, 2017). Household transportation mainly uses petroleum and gas, and higher transportation levels trigger higher carbon emissions, leading to significant environmental concerns (Anderson et al., 2017; Liang et al., 2007; Xu et al., 2015; Li et al., 2016).

However, it is observed that the number of electrical devices and vehicles is growing due to changing lifestyles and behaviors. It may be considered an increase in living standards, but this unplanned growth also plays a crucial role in GHG emissions (Olabi et al., 2023). The policy challenges surrounding domestic energy consumption and fuel choice are most important due to their substantial ramifications on public health, environmental sustainability, and climate change. Approximately one-third of the global population, which amounts to 2.3 billion individuals, depend on an open fire or inefficient stoves that are powered by kerosene, biomass (such as wood, animal dung, and crop waste), and coal for their cooking requirements (IEA, 2022).

There is a notable difference in the accessibility of cleaner cooking options between urban and rural regions. Using solid fuel stoves, prevalent among approximately 3 billion individuals residing in low and middle-income nations, is a significant factor in generating Household Air Pollution (HAP) (World Health Organization, 2018). The emission of air pollutants resulting from the combustion of solid fuels in residential settings has significant implications for climate change, both at the regional and global scales (HEI, 2019). The acceleration of the transition from solid fuel to cleaner alternatives such as gas and electricity is a crucial focus of various stakeholders, including governments, international donors, private companies, and civil society organizations (Johnson & Chiang, 2015; Rosenthal et al., 2018; Snider et al., 2018).

The transition of household fuels in developing countries from polluting and conventional fuels to environmentally friendly and contemporary alternatives has increased significant research interest. In recent decades, there has been a substantial increase in the accessibility and utilization of clean fuels. Nevertheless, the continued utilization of solid fuels persists, even among households that mainly report using environmentally friendly fuels. The term used to describe this occurrence is "stove stacking," which involves households simultaneously using conventional solid fuel stoves and cleaner alternatives. Although there have been improvements in the adoption of clean energy, the practice of stacking stoves demonstrates an intricate behavioral pattern that emphasizes the difficulties in entirely shifting away from conventional and less effective cooking techniques (Gould & Urpelainen, 2018; Ruiz-Mercado & Masera, 2015).

Extensive research has been conducted on the factors influencing the adoption of clean fuels in households, revealing various determinants of energy use behavior. These factors include demographic characteristics, socioeconomic factors, biophysical factors such as forest cover and resource availability (proximity to fuel wood sources), geographical factors (state/district distinctions and rural/urban distinctions), and financial incentives, energy and stove prices (Karakara & Dasmani, 2019; Adusah-Poku & Takeuchi, 2019; Snider et al., 2018; Ruiz-Mercado & Masera, 2015; Lewis & Pattanayak, 2012). A limited body of knowledge exists regarding the precise factors that prompted households to cease the utilization of conventional solid fuels. Identifying these factors is essential in developing focused interventions and policies to facilitate a comprehensive shift towards cleaner cooking practices.

Literature reveals that around 30 % of anthropogenic climate change is linked to food consumption (Song et al., 2015; Veeramani et al., 2017). Meat and dairy make the most significant contribution to carbon emissions in the diet (Wallén et al., 2004; Millward & Garnett, 2010). The differences in household eating preferences can be observed between and within nations and are induced by cultural and regional preferences (De Ruiter et al., 2014; Van Kernebeek et al., 2014; Hallström et al., 2015; Chalmers et al., 2016; Rose et al., 2019; Veeramani et al., 2017). Hence, exploring the connection between eating guides and carbon emissions is essential. (Yu et al., (2023).

The consumption patterns of energy fuels, transportation and food consumption significantly vary across rural-urban areas, particularly in developing countries (Kavi et al., 2013; Lacey et al., 2017; Kauffman et al., 2023). This implies that per-household carbon footprints widely differ in rural-urban areas because rural households rely predominantly on traditional cooking fuels such as wood, straw, animal waste and coal, combusted in poorly designed and inefficient cookstoves, resulting in high emissions. However, urban households are comparatively dependent on clean cooking fuels such as charcoal, LPG and natural gas (Fan et al., 2013; Kadian et al., 2007; Lacey et al., 2017; Oyeniran & Isola, (2023); employing fewer smoke. The share of carbon footprints from cooking fuels is expected to be higher in rural areas than in urban areas.

Rural-urban energy consumption patterns depend on living standards and lifestyles, leading to differences in GHG emissions (Gupta, 2011). The economic activities in rural areas are less energy intensive, which mainly drives the utilization of household transportation and electricity, employing fewer carbon footprints than in urban areas. Worldwide statistics indicate that the urban population (more than 60 %) dominates the rural population. Still, in developing countries, the trend is the opposite, where the share of the rural population is 65 % (Büchs and S. V. Schnepf, 2013). Instead of having a high rural population in developing countries, it is hypothesized that their contribution to carbon footprints is less (Kumar & Viswanathan, 2013; Bhoyar et al., 2014; Ivanova et al., 2017).

Several studies have been carried out on estimating carbon footprints and their impacts on climate change worldwide (Druckman, 2008; Kumar & Viswanathan, 2013; Wiedenhofer et al., 2013; Bhoyar et al., 2014). However, research on GHG emissions from the household sectors must be addressed in Pakistan. There is an imperative need to carry out research to mitigate GHG emissions at the household level from a development perspective. This research aims to better understand GHG emissions by examining the rural and urban consumption patterns in each of the four provinces.

The household consumption pattern is chiefly influenced by various underlying factors such as socio-economic and demographic characteristics. These socio-demographic characteristics include income, location and house size, automobile ownership, food consumption patterns, and socio-cultural differences (Minx et al.,2013; Ahmad et al., 2015; Chalmers et al., 2016; Xu et al., 2015). Urban and rural households differ in consumption behavior of electricity, cooking fuels, and mode of transportation (Minx et al., 2013; Lin et al., 2015; Xu et al., 2015), employing that household location is also expected to have a relationship with carbon footprints. The study of household influencing factors helps to answer the question, i.e., what are essential determinants of a household's carbon footprints?

The levels of carbon emissions, regarded as a constituent of the Earth's atmosphere, can exhibit variability in response to alterations in geographical positioning. The premise is that interconnectedness between neighboring areas can guide our inquiry into the spatial organization of household carbon emissions. Hence, the environment of adjacent provinces and districts affects each other and is interlinked. Spatial evaluations enable us to uncover patterns that are invisible or difficult to distinguish (Lan et al., 2023; Farrow et al., 2005). Disparities in economic and social well-being have been identified and reported within countries and across regions in the context of spatial analysis. Despite its classification as a middle-income country, Pakistan exhibits significant differences in development levels across its sub-national regions. Compared to Punjab and Sindh, Baluchistan and Khyber Pakhtunkhwa exhibit relatively lower levels of development. Pakistan is a country that exhibits substantial regional variations in urbanisation, economic development, and energy intensity. These disparities in growth may sometimes cause significant disparities in consumption patterns, carbon emissions and urbanisation at provincial and community levels. The impacts of carbon emissions exhibit significant variability across provinces owing to substantial disparities in resources and infrastructure (Waris et al., 2023). Therefore, a question arises: What are the spatial patterns of household carbon footprints at the community level in Pakistan?

Investigating the correlation between environmental effects and economic growth has prompted the recognition of environmental deterioration and increased awareness of its implications among economists. Several studies have established empirical evidence supporting a curvilinear relationship, commonly referred to as a 'U' shape, between the environmental quality of a nation and its level of income (Stern, 2004; Bravol & Marelli, 2007; Cox et al., 2012; Necula, 2023). The theoretical correlation between economic growth and carbon emissions is called the Environmental Kuznets Curve (EKC). The concept referred to is commonly known as the Kuznets curve, proposed by Nobel Laureate Simon Kuznets in 1955. Kuznets hypothesized the existence of an inverted 'U' connection between income inequality and economic development. According to this hypothesis, income inequality tends to increase initially and decrease as a country progresses in economic development. The concept of the EKC was first introduced in the early 1990s through revolutionary studies conducted by Grossman and Krueger (1991). Subsequently, Grossman and Krueger (1995) revised the concept of the EKC and posited a curvilinear association, specifically an inverted U-shape, between per capita income and pollution levels (Wang & Li, 2023).

The scope of EKC at the household level is explained as the higher income level may first increase the demand for solid fuels (fuel wood, animal dung and crop residues), and then polluted sources of energy are replaced with cleaner ones (i.e., natural gas, LPG biogas and electricity)(Cox et al., 2012b; Giovanis, 2013). This explains that people start giving value to a clean environment at certain income and consumption levels, and higher income motivates them to consume environment-friendly products (Khan et al., 2023; Khan et al., 2021; Talwar et al., 2020). It implies that environmental pollution has started to decline. Does the EKC exist for household consumption patterns in Pakistan?

1.2 Research Gaps

A wide variety of literature is available on EKC at the macro level in Pakistan, and these studies hypothesized the EKC to investigate the relationship between carbon emissions and economic growth (Ahmed & Long, 2012; Nasir & Ur Rehman, 2011; Nazir et al., 2018; Shahbaz et al., 2012). According to our knowledge, only a study by Chaudhuri and Pfaff (2002) yields an inverted U-shaped relationship between indoor air pollution and income, i.e., the existence of EKC at the household level. This study considered only the indoor pollution caused by households' cooking fuels, implying that EKC was tested at the household level by considering partial consumption. Still, the present study attempts to fill this gap by considering carbon emissions from complete consumption patterns. In particular, this study tested the EKC hypothesis in Pakistan using carbon emissions from household-level consumption, i.e., energy consumption (gas, electricity, petroleum products, coal, and biomass).

The household-level carbon emissions analysis is essential to help policymakers make efficient and effective policies to reduce household carbon emissions (Roberts, 2008; Zhang et al., 2014). Several studies extensively analyzed the connection concerning urban growth, aggregate energy use, and carbon emissions (Hertwich & Peters, 2009; Levitt et al., 2017). These studies have used macro-level data to estimate carbon footprints. However, studies deal with developed nations' carbon emissions and energy consumption (Kennedy et al., 2014a; Wiedenhofer et al., 2013). However, such studies must still be included in developing countries like Pakistan. Recently, a concerted endeavor has been made to comprehend the carbon emissions specifically emanating from urban households (Ahmad et al., 2015; Hasan & Zhang, 2018) by considering consumption. The current study addresses the existing research gap by examining the correlation between household consumption and carbon emissions from direct sources (electricity and cooking fuels) and indirect sources (food). Additionally, the study contributes by conducting a comparative analysis of urban and rural carbon footprints in four provinces (Punjab, Khyber Pakhtunkhwa (KPK), Sindh, and Baluchistan), encompassing both direct and indirect forms of pollution (Chishti et al., 2023; Adebayo et al., 2021).

Carbon emissions can vary with changes in geographic location. In Pakistan, most of the spatial carbon emission studies focus on agriculture, urban air and water quality, etc. (Ahmad et al., 2011; Bhowmik et al., 2015; Ghauri et al., 2007; Irfan et al., 2015; Malik et al.,2010; Qaiser et al., 2018; Shakeel et al., 2015; Xu et al., 2020)), while ignoring the spatial variation in carbon emissions caused by household sector. It is essential to analyze the spatial factors influencing household carbon emissions at the community level to develop future national and regional carbon reduction targets.

1.3 Research Questions:

The research addresses two essential questions based on the research gaps in the field.

1. what are direct and indirect carbon footprint estimates together with their household consumption determinants which include demographic factors and economic status and spatial patterns in Pakistan?
2. What effects choice of cooking fuels has on household carbon footprints as well as how emissions spread across households and their behavioral patterns?

Multiple auxiliary questions supplement the central research inquiries to extend the understanding of the problem while supporting policy recommendation development. These include:

- Is there evidence that the Environmental Kuznets Curve hypothesis demonstrates the connection between cooking fuel consumption and related emissions in Pakistan?
- How the food consumption patterns, emission levels, and price elasticities help explain consumer choices regarding sustainable food choices.
- What Strategies for sustainable cooking fuel practices can be created by analyzing the impacts of fuel consumption?

The supplementary collection of data aims to extend understanding about factors affecting emissions at the household level in Pakistan beyond the core research objectives.

1.4 Research Objectives:

In the light of the above discussion, the objectives of this study are to:

- Estimate household consumption's direct and indirect carbon footprints and their determinants in Pakistan.
- To investigate the presence of the Kuznets curve phenomenon in Pakistan by examining emissions from cooking fuel consumption.
- To analyze fuel and food consumption and substitution dynamics in Pakistan.
- Propose carbon mitigation strategies in Pakistan at household levels by integrating the consumption and substitution dynamics.

1.5 Rationale Behind the Structure of Research Objectives

The research adopts a logical structure with specific stages that start with empirical research, followed by theoretical validation then end with practical implementation. The objectives in this research display interdependent growth that enables a coherent development of methods from start to end.

The first objective measures direct and indirect household carbon footprints and identify their determinants. This foundational analysis establishes the basis for the entire study. Understanding household emissions and the factors driving them is essential to recognize patterns of consumption and emission behavior. Any attempt at substitution analysis or theoretical application without this initial groundwork would lack theoretical stability.

Building upon this base, the study next examines the Environmental Kuznets Curve (EKC) hypothesis, with a specific focus on emissions from cooking fuels. This analysis explores how rising income and changes in consumption behavior influence fuel choices and related emission patterns.

Following the theoretical examination, the research proceeds to investigate how consumers substitute between fuel and food consumption choices. This objective aims to uncover preferences for energy sources and dietary habits, as well as the motivations behind these choices. Social and behavioral aspects of energy use and eating habits directly shape future emission trends and offer critical insights for policy formulation.

1.6 Significance and Contribution of the Study:

The present research aims to advance the understanding of carbon emission estimation by examining rural and urban household consumption levels in Pakistan. We establish the current spatial and temporal patterns of carbon footprints through estimating their composition at the provincial level and contrasting their changing consumption behavior over time between the rural and urban sectors. A deep understanding of drivers of carbon footprint is needed to execute targeted policies for lowering aggregate emissions.

The study then makes estimates of the carbon footprint-income interaction, investigating the Environmental Kuznets Curve (EKC) hypothesis at both the rural-urban and provincial levels. Last but not least, this research presents new evidence on patterns of fuel and food consumption, estimating their substitutability and integrating the analysis with emissions to search for the right mitigation policies.. based on the study objectives, this study makes three significant and testable contributions to development economics and climate change literature: This research builds the first complete demand system (e.g., QUAIDS/AIDS) that estimates household expenditure on both direct emissions (from fuel) and indirect emissions (from food) using micro-level household survey data in Pakistan.

This framework extends beyond consumption analysis to identify the climate effect of household consumption decisions. The study provide the first quantitative cross-price elasticity estimates of high-emission foods (such as red meat) and clean energy (such as LPG). This new measure is applied to empirically validate the economic scale for cross-sectoral policy measures utilizing price fluctuations in one commodity group to create environmentally more favorable substitution in a different consumption groups.

The research is divided into six different chapters. Chapter 1 presents information about the research topic by describing its background and lists the main study goals and research questions. Chapter 2 integrates numerous theoretical approaches and existing studies related to the research topic with a comprehensive policy examination. Chapter 3 explains the research methodology including research design, data collection and research analysis methodsto investigate the research questions. Chapter 4 presents study results and discussion. Chapter 5 reviews all existing policies. Finally Chapter 6 concludes the thesis by summarizing key insights along with analytical-based conclusions and practice and policy recommendations.

Chapter 2

LITERATURE REVIEW

Much research has been conducted on estimating a household's Environmental Kuznets Curve (EKC) hypothesis, household carbon footprints, their factors, and spatial carbon emissions. The literature attempted to test the EKC hypothesis, which assumes that environmental degradation rises in the early phases of economic development until a certain income level. Then, there will be an environmental improvement.

The rapid economic growth of industrialization has led to substantial carbon emissions (Ansari, 2022). These emissions trigger natural events such as global warming and climate change, which pose severe threats to human health and the environment (Meinshausen et al., 2022). Countries are currently making every effort to mitigate carbon emissions. Identifying the factors that mitigate carbon emissions is critical for sustainable growth (Chopra et al., 2022). In this regard, the Environmental Kuznets (EKC) hypothesis describes an "inverted U-shaped" curve between income levels and carbon emissions. In the first stage, carbon emissions increase and reach a certain point (called the turning point) as income increases.

After the turning point, the increase in income can reduce carbon emissions and enter the second stage. EKC hypothesis explores the effect of income levels on carbon emissions in the long run, incorporating the economy and the environment into a consistent research framework (Panayotou, 1993). The 2030 Agenda for Sustainable Development was adopted consistently by 193 countries globally in 2015. The agenda states that achieving sustainable development requires a joint effort in three dimensions: economic, environmental and social (UN, 2015). Therefore, it is necessary to incorporate more factors into the EKC research framework to identify factors that mitigate carbon emissions from economic, environmental, and social dimensions.

The EKC hypothesis was initially used to describe the relationship between economic growth and income inequality (Kuznets, 1955). In the last three decades, the EKC hypothesis was extended to the environmental field and formed the environmental EKC hypothesis. The environmental Kuznets hypothesis describes the relationship between economic growth and environmental degradation. It is argued that the relationship between income and environmental pollution has a threshold. Before the threshold, the increase in income leads to increased pollution. When environmental pollution reaches the threshold, a further income increase leads to reduced pollution. In this regard, scholars have explained that the initial growth brought about structural changes and increased energy consumption demand, thus leading to environmental pollution. However, further growth causes technological changes. These technological changes can promote environment-friendly technologies and institutional policies and improve the environment (Dinda, 2004).

Grossman and Krueger (1991) were the pioneering researchers who discovered an inverse U-shaped curve that examined the relationship between per capita income and pollutants. The initial body of research on the Environmental Kuznets Curve (EKC) primarily focused on analyzing localized air pollution emissions. Following this, the scope of analysis was expanded to encompass worldwide pollution, the accumulation of waste, and the depletion of natural resources. Early empirical investigations revealed the presence of a U-shaped relationship between national income and environmental quality, indicating that economic advancements may result in environmental enhancements (Beckerman, 1992; Bhagawati, 1993)(Javid & Sharif, 2016; Lenzen et al., 2006), investigated by the EKC hypothesis. Their results do not favour the hypothesis of the EKC; however, they claim that energy use increases monotonically owing to increased consumption and demonstrate no turning point. A amount of literature on EKC is also available in Pakistan. According to Shahbaz et al. (2012), there is evidence of a long-term association between carbon emissions, energy consumption, economic growth, and trade openness in Pakistan. Additionally, the study supports the hypothesis of the EKC. Ahmed and Long (2012) provided empirical evidence supporting the positive correlation between environmental degradation and economic growth.

The household's EKC in different areas is studied in different periods, so their findings differ on the EKC's existence and characteristics (Baiocchi et al., 2010; Girod & Haan, 2010). Moreover, using the micro-household level data, it was observed that carbon emissions continue to decrease with a rise in income level to a certain level; however, higher income levels might result in more emissions (Martínez-Zarzoso & Bengochea-Morancho, 2004). Apart from this, a simple static model of the micro-foundations of the connection between the consumption of a required product and the reduction in unwanted pollutants (Kahn, 1998; Andreoni & Levinson, 2001; Kahn & Schwartz, 2004; Cox et al., 2012).

Empirical evidence regarding the potential relationship between household emissions and income remains ambiguous when examined in detail. On the premise that technological advancements can effectively reduce vehicle emissions, it can be inferred that newer automobiles generate fewer environmentally detrimental emissions. Higher-income households tend to possess newer vehicles and utilize them more frequently. However, they also demonstrate a greater likelihood of owning newer vehicles that generate lower detrimental emissions. Although studies have examined the household level EKC in developing countries such as Pfaff et al. (2004) on fuel consumption, there needs to be more research on this subject in developed countries. Chaudhuri & Pfa (2002) researched cooking fuel emissions used by homes in Pakistan and discovered the existence of EKC by the connection between indoor air pollution and earnings based on Pakistan's micro information.

The research demonstrated an inverted-U connection concerning indoor air pollution and earnings under reasonable expectations about the emissions caused by fuel use. Using information from the National Sample Survey for 1983, 1993–1994 and 1999–2000. However, the study did not use other primary emissions sources (direct and indirect) or other significant emissions sources (direct and indirect); hence, the study may underestimate the level of total household emissions.

The comprehensive collection of analyzed articles has identified various variables affecting carbon emissions and household energy use. These include socioeconomic factors, household characteristics, and geographic factors: age, household income, education level, household size, gender and geographic location. At the micro (household) level, studies estimated the impact of demographic, socioeconomic factors and changing consumption patterns. Serino and Klasen (2015) examined household carbon footprint determinants in the Philippines, which confirmed that family income is the primary determinant of emissions.

Lin et al. (2013) analyzed the significant determinants of GHG emissions from households in Xiamen City; the findings showed that the primary influencing variables were housing area and family size. Qu et al. (2013) reported that household carbon levels increase with family size and income. Han, Xu, and Han (2015) analyzed household-level determinants of fixed carbon emissions in China (urban) and discovered the most significant determinant to be family income. Xu et al. (2015) used study information to assess urban household carbon emissions and contributing factors in the Yangtze River Delta, and findings identified family income, household area, family size and age composition as the main influencing aspects.

Several studies have demonstrated a significant disparity in carbon footprints between wealthy households and those with lower incomes (Druckman & Jackson, 2009; Weber & Matthews, 2008).

The study conducted by Sovacool and Brown (2010) revealed that the primary factors contributing to variations in carbon footprints were per capita income, population density, transportation modes, and electricity and power supply. Jones and Kammen (2011) discovered that income level and household size were the most significant factors for estimating carbon footprints. According to Jones & Kammen (2011), income level and household size were the best predictors of carbon footprints (Tukker et al., 2010; Chalmers et al., 2016; Sulaimon, 2018), and income is considered one of the most critical determinants (Gough et al., 2011; Büchs & Schnepf, 2013; Chitnis et al., 2014; City, 2015).

The literature discussed above shows that higher income levels correlate with emissions, so it appears to reflect the need of wealthier households for more commodities because of the upper-income level. Larger homes, more expensive cars, and more comfortable indoor spaces and outdoor opportunities are more likely to be pursued (Tukker et al., 2010; Chalmers et al., 2016; Sulaimon, 2018), and income is considered one of the most critical determinants (Gough et al., 2011; Büchs & Schnepf, 2013; Minx et al., 2013; Chitnis et al., 2014; City, 2015; Li et al., 2016). The diverse age groups have been correlated with distinct income levels and consumption patterns.

Some literature suggests that old age people have higher carbon emissions, direct and indirect, by keeping income as a controlled variable. It may indicate that higher income does not direct the carbon emissions. Instead, age is the defining factor for higher carbon emissions. However, some studies indicate that household size is vital to carbon emissions. The larger size emits the same emissions as the one to two household sizes because household energy consumption increases with income rather than household size, as income has a stronger relationship than the number of household members. Research on the correlation between the educational attainment of individuals within households and carbon emissions has yielded inconsistent findings.

There are contrasting viewpoints regarding the relationship between higher levels of education and emissions. One perspective posits that an increase in education is associated with elevated emissions. In contrast, an alternative viewpoint suggests that greater educational attainment can contribute to reducing pollutants at the household level. However, higher education is positively related to more convenient energy sources and increased travelling, emitting more. Based on the discourse encompassing carbon emission factors, it is evident that households with higher incomes tend to prioritize the acquisition of larger residences, expensive vehicles, enhanced indoor environments, and increased engagement in recreational pursuits. These lifestyle choices are significant contributors to carbon emissions.

However, the impact of age appears to be ambiguous. Household Carbon Emissions(HCEs)also increase with household size and education level. Emissions from energy consumption have been extensively explored (Kadian et al., 2007; Druckman & Jackson, 2009; Büchs & Schnepf, 2013; Minx et al., 2013; Pachauri, 2014; Ahmad et al., 2015; Papachristos, 2015; Oladokun & Odesola, 2015) but food-based emissions have been explored less intensively (Kim & Neff, 2009; Chalmers et al., 2016; Veeramani et al., 2017; González-García et al., 2018).

The majority of research endeavors focus on the examination of household emissions from a consumption perspective. This approach encompasses all emissions associated with household consumption within a particular country, regardless of whether they originate domestically or internationally. Hertwich and Roux (2011) examined the climate implications associated with GHG emissions throughout the lifecycle of household electronic equipment. In contrast, Panzone et al. (2013) developed an index that assesses the ecological sustainability of household food consumption by utilizing scanner data obtained from a food retailer in the United Kingdom and consumer preferences.

On the other hand, the production perspective considers the emissions generated within a specific country, irrespective of the location where final commodities are consumed. According to Druckman and Jackson (2009), a distinguishing factor between these two methods lies in the emissions embodied in trade. Early research by Hosier and Dowd (1987) using a multinomial logit model for household fuel choice in Zimbabwe demonstrates that while economic variables impact fuel decisions, many other variables are also important. Moreover, much of the latest literature shows that fuel conversion is often not complete and is, in reality, a gradual method in which many households frequently use various fuels.

The reasons for various fuel use are diverse and not dependent on economic variables alone. However, the energy service's affordability or price also significantly impacts the household's decision. Households sometimes use more than one fuel to secure the supply throughout. Sometimes, the decision may depend on cultural, personal or taste choices.

Park and Hto (2007) estimated that 60 % of energy consumption in Korean households is due to indirect consumption. Markaki et al. (2017) studied the indirect emissions of Greek households and revealed that more than 70 % of the household carbon emissions are due to indirect consumption sources. The urban and rural carbon emissions also vary based on socioeconomic, demographic and household characteristics. Hence, it is imperative to investigate the carbon emissions produced by households living in rural and urban areas. Cities are responsible for approximately 78 % of global greenhouse gas (GHG) emissions. According to Lebel et al. (2007), urban areas in developing countries exhibit higher emissions levels than rural areas, primarily due to higher incomes and smaller family sizes.

This section explores the conceptual and theoretical frameworks that form the foundation for examining household fuel consumption in developing nations. Several current models depend on the 'energy ladder' notion to clarify the consumption of fuel by households in developing nations. The energy ladder is a fundamental framework utilized in these models, depicting households' advancement from conventional fuels to intermediate alternatives and ultimately to contemporary fuels as their economic circumstances ameliorate. The metaphorical ladder illustrates a progression in which households, as their income increases, progress through various stages of fuel transition.

These stages involve shifting from conventional sources like biomass to intermediate alternatives like kerosene or coal and adopting contemporary fuels like gas and electricity (Heltberg, 2005; Chambwera & Folmer, 2007; Lay et al., 2013). The energy ladder concept expands upon the income effect of consumer theory by demonstrating that as income increases, consumers replace essential goods and luxury items with inferior alternatives. This framework offers a simplified depiction of how households adapt their fuel preferences in response to shifting economic conditions.

Masera et al. (2000) critiqued the energy ladder theory, arguing that it needs to capture the complexities of households' fuel consumption patterns sufficiently. They argued that fuel stacking is widespread in developing countries' urban and rural areas. Fuel stacking involves households implementing various fuel-use patterns and selecting a blend of fuels from lower and higher energy hierarchy tiers. The perspective presented in this study questions the prevailing belief that modern fuels are invariably flawless replacements for conventional fuels. Instead, it suggests that modern fuels may only function as partial substitutes (van der Kroon et al., 2013, 2014). The occurrence of concurrent fuel utilization can be ascribed to a multitude of factors, encompassing sporadic scarcities of contemporary fuels (Kowsari & Zerriffi, 2011), the exorbitant expenses linked to sole dependence on modern fuel devices, fluctuations in commercial fuel prices, and household inclinations that deter complete embrace of modern fuels (Masera et al., 2000). The complexities inherent in the process of fuel switching suggest that, in addition to income, numerous factors exert influence on fuel consumption.

Edwards and Langpap (2005) and Gupta and Köhlin (2006) developed household consumer models that were explicitly designed to depict the simultaneous consumption of non-commercial and commercial fuels in urban settings. These models function using the principles of maximizing consumers' utility while considering a budget constraint, highlighting the significant influence of prices on households' fuel consumption patterns. The selection of consumption goods being examined is based on the investigated contexts. Fuel consumption is commonly perceived as solely influenced by income, market prices, and household preferences. Nevertheless, this method presents difficulties in understanding the integration of non-market fuels, such as firewood and straw, into household choices and their interaction with agricultural practices related to these commodities.

In light of these constraints, several scholars have proposed a more complex theoretical framework suitable for comprehending fuel consumption in rural households. Households in developing countries and rural areas need help accessing a wide range of goods and services due to the incompleteness of markets. When markets are not fully integrated, the decisions regarding allocating resources for production and consumption become interconnected, particularly regarding fuel sources and agricultural products. In this theoretical framework, rural households are represented as individuals who strive to maximize their utility, considering constraints such as limits on leisure and budget, an agricultural production function, a function for producing residue and dung, and a function for collecting fuel wood.

Heltberg et al. (2000) examine the issue of market failures relating to crop residues, animal dung, and labour, which investigates the replacement of firewood with privately produced non-marketed fuels, such as animal dung and crop residues, with a specific focus on addressing the increasing scarcity of firewood. Chen et al. (2006) expand upon the methodology proposed by Heltberg et al. (2000) by introducing the concept of the missing market for firewood, emphasizing the substitution dynamics between firewood and coal. Manning and Taylor (2014) investigate the issue of labour market failure in rural areas and the process of substituting firewood with gas. In conclusion, Muller and Yan (2014) propose a comprehensive decision model incorporating fuel use decisions alongside agricultural production, domestic technology, fuel collection technology, and fuel rationing combined.

Tobler (1970) introduced the initial principle of geography, positing that "*everything is related to everything else, but near things are more related than distant things*" Nevertheless, it is essential to note that this proposition does not enjoy universal consensus. The assumption that adjacent observations are linked can help to direct our investigation into the spatial structure of household carbon emissions.

Studies show that cities exert disproportionately elevated economic stress regarding waste and emissions compared to their spatial extension. However, this image could alter relative to a per capita basis (Dodman, 2009; Hoornweg et al., 2011). Higher income levels increase household consumption, a source of GHG emissions. Household GHG emissions are accounted as 'indirect emissions'. The rural regions use traditional fuels such as wood, animal waste and crop residues, which have local economic effects owing to substantial pollutant emissions such as SO2, N2O, etc., along with GHG emissions such as CO_2, CH_4, and N_2O. Many studies focus on the correlation between carbon emissions and urbanisation and have shown mixed results (Liddle, 2014; Zhang & Zheng., 2014; Zhang et al., 2017).

Some researchers suggest that energy use is increasing due to urbanisation and carbon emissions in several developing and developed countries (Al-Mulali et al., 2013); they have posited that the process of urbanisation is likely to result in higher amounts of energy consumption and carbon emissions across various developed and developing nations. The increasing urban growth necessitates a substantial number of public and private facilities, consequently leading to an increased demand for energy. The impact of urbanisation on carbon emissions was influenced by the disparity between urban and rural lifestyles, as observed through the lifestyle approach (Feng et al., 2011; Xu & Lin, 2015).

Using various quantification methodologies to estimate carbon footprints may result in disparate outcomes (Plassmann et al., 2010; Dias & Arroja, 2012). Several methodologies were employed to examine household consumption activities, including input-output models, life cycle assessment, and emission coefficient methods. These approaches are widely utilized to measure household consumption emissions (HCEs). Consumption data derived from consumer expenditure surveys is frequently employed to quantify emissions from consumption activities.

Wei et al. (2007) employed the consumer lifestyle approach (CLA) to investigate the impact of urban and rural residents' way of life on energy use, energy and energy use, and subsequent emissions in China. The linear multiplier factor method was employed to estimate the direct emissions of household energy consumption. Furthermore, determining indirect GHGs entails multiplying the carbon emission intensity associated with every sector by corresponding consumption spending. However, the CLA approach reflects the effects of the entire lifecycle of a product. However, it requires an extensive data set of the entire lifecycle, which is time-consuming, and the data set availability is the critical problem.

Kerkhof et al. (2009) utilized a hybrid approach that integrated physical-chemical process analysis and economic input-output approaches. Their objective was to determine the level of carbon emissions particular to each country's different industries. After that, all industries' carbon emission intensity was associated with the national consumption expenditure data to estimate the average household CO_2 emissions in specific countries. The indirect emissions resulting from household consumption were estimated by Liu et al. (2011) using the input-output method.

The methodology prescribed by the IPCC was employed to quantify the direct emissions arising from household consumption. The research employed the logarithmic mean division index (LMDI) method to examine the effects of fluctuations in the identified independent variables on indirect emissions arising from household consumption. Han et al. (2014) utilized the input-output expenditure method to quantify the carbon emissions embedded within a given system, and the research period encompassed applying the ordinary least squares regression model and quantile regression to examine the determinants of per capita household embedded carbon emissions (HECEs).

Robbie et al. (2009) referred to as "multiregional input-output analysis". It has been employed to quantify the emissions of exports and imports. Nevertheless, uncertainties can accumulate when sectors are combined (Green Design Initiative, 2008; Matthews et al., 2008b).

Nevertheless, the application of the input-output model for micro-level implementation is constrained. According to Wiedmann and Minx (2007), it was found that the input-output model offers a standardised analytical framework that can be universally applied to diverse populations. The present methodology exhibits limitations regarding its reliability for predicting long-term outcomes, as it presupposes a constant technology coefficient that fails to account for technological advancements and changing elasticity over time.

GHG data can be obtained by conducting direct onsite real-time measurements or by making estimations using emission factors and models, commonly employed techniques. Generally, emissions from products, organizations, and events are assessed using specific emission factors and models. These tools rely on data on fuel consumption, energy usage, and other contributing factors that ultimately result in emissions, focusing on carbon dioxide (CO_2) emissions. Emission factors can be found for various industrial processes and land uses in the GHG protocol, PAS-2050, and IPCC (2006).

Consequently, it has been suggested to utilize region-specific emission factors and models, as recommended by WRI/WBCSD (2004) and IPCC (2006). The lifecycle process model can be characterized as a bottom-up approach, which incorporates all stages of the product life cycle, encompassing production through product disposal, which is logically posited as the most precise model. On a product-specific level, the process model exhibits greater accuracy compared to the input-output model. The methodology necessitates comprehensive data about the product's complete life cycle, rendering it a costly endeavor in terms of time and computational resources. One significant drawback associated with the process model pertains to the frequent unavailability of necessary data, thereby leading to diminished levels of accuracy.

Several studies discussed above estimated determining factors of household carbon emissions using the OLS regression methodology. However, there are still two things that could be improved. In the first place, the OLS regression method views the impacts of household attributes as uniform regarding carbon emissions. Nevertheless, it is doubtful that low and high-carbon households are equally prone to changes in household characteristics. Second, the OLS regression method cannot demonstrate the size of the contribution of household characteristics to the variations in household carbon emissions. The second method used for the estimation of determinants is quantile regression. The coefficients of quantile regressions explain marginal change compared to OLS, which assigns a constant marginal impact across the entire distribution of response variables (Koenker & Bassett, 1978; Koenker & Hallock, 2001; Han et al., 2015).

The literature examined the correlation between carbon emissions and household income, particularly emphasizing the Environmental Kuznets Curve (EKC) hypothesis. The Environmental Kuznets Curve (EKC) hypothesis proposes a negative U-shaped relationship between income levels and carbon emissions. It argues that environmental degradation increases with economic growth until a certain threshold is reached, after which additional growth results in environmental improvement. The significance of comprehending these dynamics in the context of sustainable development is underscored in the review, which is consistent with the 2030 Agenda for Sustainable Development.

The EKC hypothesis, which Kuznets initially postulated in 1955 regarding economic growth and income inequality, has developed in the past thirty years to incorporate environmental considerations. The 1991 seminal work by Grossman and Krueger established the groundwork for examining the correlation between pollutants and per capita income. Nevertheless, further empirical inquiries have produced inconclusive findings, which cast doubt on the EKC hypothesis and emphasize the necessity for a more nuanced comprehension.

The literature places significant emphasis on the influence of socioeconomic factors, household characteristics, and geographic elements concerning household emissions. A correlation exists between higher income levels and increased emissions, which can be attributed to household consumption habits. Nevertheless, the influence of age on emissions is still uncertain, as certain studies propose that older individuals produce more significant emissions. The review emphasizes the importance of variables such as household size, level of education, and consumption patterns in shaping carbon footprints.

The article examines the diverse results concerning the correlation between education and emissions, presenting opposing viewpoints on whether a higher education system contributes to reducing pollution. The production perspective is country-specific, whereas the consumption perspective predominates in research, including emissions associated with household consumption. Urbanisation and other spatial factors significantly influence carbon emissions. Urban areas, which contribute significantly to worldwide greenhouse gas emissions, demonstrate higher levels than rural regions, owing to variables such as reduced family sizes and greater incomes. In addition, the literature recognises the significance of estimating carbon footprints using various methodologies that emphasize the necessity for region-specific approaches and the difficulties related to data accessibility.

Chapter 3

METHODOLOGY

The theoretical framework of this thesis is grounded in established micro-econometric principles, moving beyond general consumer theory to provide a robust, empirically testable structure for linking household demand to environmental outcomes. For the analysis of budget allocation, we employ the Almost Ideal Demand System (AIDS) model, introduced by Deaton and Muellbauer (1980), which is essential for deriving price and expenditure elasticities required to understand how households substitute between competing energy sources and food groups. Furthermore, the analysis of energy transition necessitates the application of concepts from development economics: the Energy Ladder Hypothesis frames our expectation that income drives households toward cleaner fuels, while the inclusion of the expenditure-squared term allows us to test the non-linear relationship proposed by the Environmental Kuznets Curve (EKC). Finally, given that many households are non-consumers of modern fuels, our modeling strategy employs the Heckman two-stage approach (Heckman, 1979) to mitigate potential sample selection bias that would otherwise render the elasticity estimates unreliable. Collectively, this specific combination of theoretical tools provides the necessary rigor to translate household choices into actionable policy insights regarding carbon emission reduction.

3.1 Conceptual Framework of Environmental Kuznets Curve (EKC):

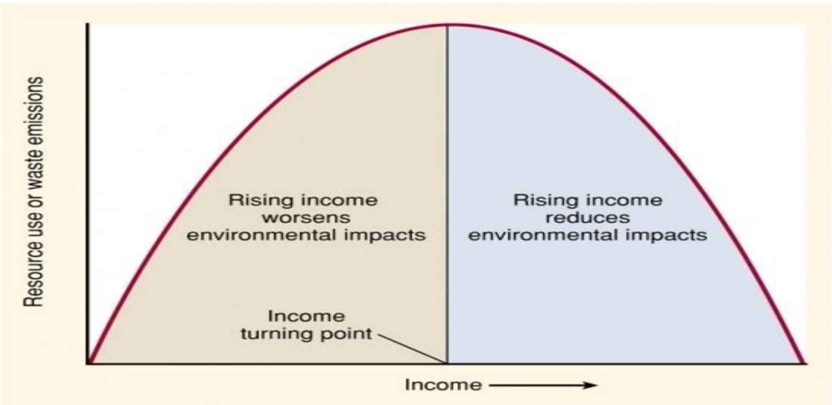
The present research is based on two critical theoretical backgrounds: the theories and hypotheses regarding the definition and determinants of carbon footprints and the theory on the Environmental Kuznets curve (EKC) of the climate.

The Environmental Kuznets Curve (EKC) illustrates the correlation between indicators of environmental degradation and per capita income, as depicted in Figure 1. The relationship between pollution and per capita gross domestic product (GDP) growth is assumed to be empirical, as posited by Unruh and Moomaw (1998), which elucidates that during the initial phase of economic advancement, there is a notable decline in environmental quality, primarily attributed to factors such as the presence of ambient air pollution, deforestation, contamination of soil and water, and various other contributing elements.

Because growing economic activities require additional energy, resources and material inputs, which also generate waste as by-products. When the economy starts to develop, income rises, and demand for a clean environment increases.

This pressures governments to develop and implement rules for a sustainable environment. Hence, the pace of deterioration slows down after achieving a certain level of income, and environmental quality starts improving (Grossman & Kruger,1991). The environment Kuznets curve graphs the hypothesis that at first, as the per capita income increases, the countries exploit the natural resources, which increases the waste emissions, and after a certain income level, the country's demands for a cleaner environment increase, as elaborated in Figure 0.1. The horizontal axis of EKC explains a country's income (growth), and the vertical axis is carbon emissions due to economic growth.

Figure 0.1 Conceptual Framework of Environmental Kuznets Curve



Source: Yandle et al. (2004)

Various research has applied EKC to estimate income inequality and environmental degradation primarily at the macro level (Stern, 2004; Zomorrodi & Zhou, 2016; Ota, 2017). However, several surveys estimated the relationship between household income and carbon emissions to explore EKC's existence at the micro level (Cox et al., 2012; Giovanis, 2013; Xu, 2014). The amount of household carbon rises with an increased income level as higher income improves consumption patterns (Heerink et al., 2001; Cropper & Griffiths, 2019). However, on the household level, the number of carbon emissions starts declining when income increases beyond a certain level (inflexion point) (Xu, 2014).

The development of the theoretical model for consumer behavior, known as the environmental Kuznets curve, was attributed to Andreoni and Levinson in 2001. The AL model adopts a consumer-oriented perspective in its Environmental Kuznets Curve (EKC) analysis and posits increasing returns to pollution abatement.

Let us consider a hypothetical individual, an agent, whose overall satisfaction is determined by consuming a private good, denoted as C, and the bad, known as pollution, denoted as P. The preferences may be presented as follows:

$$U = U(C, P) \tag{3.1.1}$$

Where UP<0; UC>0 and U is quasi-concave in P and C. Pollution, a consequence of consumption, presents an opportunity for consumers to mitigate its effects through resource allocation. This can be achieved either by investing resources in cleaning up pollution or by proactively preventing its occurrence.

The consumer resources for environmental efforts are E, which includes awareness of consumers, clean technology, and carbon taxation. Pollution is, therefore, a function of increased consumption and decreased environmental efforts:

$$P = P(C, E) \tag{3.1.2}$$

Suppose the representative agent possesses an endowment denoted as Y, i.e., resources that can be allocated towards consumption (C) and environmental efforts (E), where $P_C < 0$ and $P_E > 0$. To facilitate the analysis process, the comparative expenses associated with consumption and environmental exertion have been normalised to a value of 1. The resource constraint becomes:

$$Y = C + E \tag{3.1.3}$$

Suppose:

$$U = C - zP \tag{3.1.4}$$

$$P = C - C^{\alpha}E^{\beta} \tag{3.1.5}$$

Let U denote the utility function, and P represents the pollution function. The equation represented by Eq. (4) exhibits linearity and additivity concerning the variables C and P. Additionally, it is assumed that $z > 0$ represents a constant marginal disutility of pollution. The variable C represents the level of gross pollution before abatement, which exhibits a direct proportionality to consumption. The expressions C^{α} and E^{β} signify the relationship between consumption and pollution, suggesting a direct proportional relationship. However, resources allocated towards environmental efforts exhibit a diminishing marginal effect on pollution reduction, as indicated by a concave production function.

Assume $z = 1$, by substituting the pollution function into the utility function; we can deduce that the individual maximizes the function $C\alpha$ and $E\beta$ while subject to the constraint $Y = C + E$. Consequently, the optimal solutions for consumption and environmental efforts can be obtained using the standard Cobb-Douglas approach as follows:

$$Max.(C, E): U = C^{\alpha}E^{\beta} \tag{3.1.6}$$

$$Subject\ to: C + E = Y \tag{3.1.7}$$

Solution:

$$U = C^{\alpha}E^{\beta} - \pi(M - C - E) \tag{3.1.8}$$

$$\frac{dU}{dC} = \alpha C^{\alpha-1}E^{\beta} + (-1)\pi = 0 \tag{3.1.9}$$

$$\pi = \alpha C^{\alpha-1}E^{\beta} \tag{3.1.10}$$

$$\frac{dU}{dE} = \beta C^{\alpha}E^{\beta-1} + (-1)\pi = 0 \tag{3.1.11}$$

$$\pi = \beta C^{\alpha}E^{\beta-1} \tag{3.1.12}$$

Setting $\alpha C^{\alpha-1}E^{\beta} = \beta C^{\alpha}E^{\beta-1}$ gives $C = \frac{\alpha E}{\beta}$ and $E = \frac{\beta C}{\alpha}$ and substituting into Eq. 3.3 gives:

$$E^* = \frac{\alpha}{\alpha+\beta}Y \text{ and } C^* = \frac{\alpha}{\alpha+\beta}Y \tag{3.1.13}$$

E^* and C^* are the optimal consumption and environment effort that maximizes utility while substituting E^* and C^* into Eq. 3.5 gives:

$$P^*(Y) = \left(\frac{\alpha}{\alpha+\beta}\right)Y - \left(\frac{\alpha}{\alpha+\beta}\right)^{\alpha}\left(\frac{\alpha}{\alpha+\beta}\right)^{\beta} Y^{\alpha+\beta} \tag{3.1.14}$$

The above expressions give the EKC. The derivative of $P^*(Y)$ gives the slope of the EKC curve.

$$\frac{dP^*}{dY} = \left(\frac{\alpha}{\alpha+\beta}\right)Y - (\alpha+\beta)\left(\frac{\alpha}{\alpha+\beta}\right)^{\alpha}\left(\frac{\alpha}{\alpha+\beta}\right)^{\beta} Y^{\alpha+\beta-1} \tag{3.1.15}$$

The signs of which depend on the parameters α and β.

The quadratic form is the necessary and sufficient econometric requirement for capturing the inverted U-shaped relationship characteristic of the EKC. Deliberately excluding interaction terms with other covariates, such as household size or demographic factors, mitigates the severe risk of multicollinearity. Including the expenditure level and its square already creates a high degree of correlation; adding interaction terms would amplify this issue, leading to unstable and imprecise coefficient estimates for the critical EKC turning point, particularly within complex non-linear frameworks (Heckman/Tobit). This parsimonious strategy is well-established in the literature. It aligns with seminal studies that used the simplest quadratic form to validate the EKC (Grossman & Krueger, 1995; Holtz-Eakin & Selden, 1995), contemporary research that explicitly advocates for testing the unconditional EKC first (Azomahou, Laisney, & Van, 2006), and recent sectoral and multi-country analyses (Taşdemir, 2024; Hasanov et al., 2024) that maintain this core quadratic specification to provide the most direct and stable test of the income-emission hypothesis. Therefore, the exclusion of interaction terms ensures the maximum statistical stability required for the precise estimation of the primary research objective.

Evaluating the effectiveness of climate change mitigation strategies in the built environment is mainly achieved by focusing on a particular source of emissions, such as transportation or heating. Such an estimation ignores the other anthropogenic activities that lead to carbon emissions. Therefore, this study aims to provide empirical evidence on carbon footprints, which can provide a clear picture of effective mitigation strategies.

3.2 Conceptual Framework of Fuel Substitution

As developing countries strive for economic growth, researchers have increasingly focused on how energy consumption in urban households is evolving.The most widely recognized framework for understanding these patterns is the energy ladder hypothesis (Leach, 1992) The energy ladder hypothesis suggests that as people's income rises, they tend to shift from using traditional fuels like wood and charcoal to more modern ones like kerosene, gas, and electricity (Masera et al., 2000). Essentially, the idea is that households move up a "ladder" of energy sources, starting with less efficient fuels and gradually switching to cleaner and more efficient options as they can afford it.

This movement is generally seen as a one-way progression, with people leaving behind "inferior" fuels for "superior" ones when they have the economic means to do so. However, empirical evidence from various studies challenges the energy ladder model, revealing significant inconsistencies. Rather than completely transitioning to modern fuels, many households engage in "fuel stacking" using a mix of traditional and modern energy sources (Smith et al., 2014)

The energy mix model offers a more nuanced view. It moves beyond the linear trajectory of the energy ladder, recognizing that fuel transitions are non-linear and influenced by a range of factors, including socio-cultural norms, access to technology, geography, and government policies (Howells et al., 2015). Under this model, households may continue to use traditional fuels for certain purposes, such as cooking, due to their affordability, availability, or cultural preference. For example, electricity may be used for lighting, while gas or biomass remains preferred for cooking because of its cost-effectiveness or availability(Kumar et al., 2018).

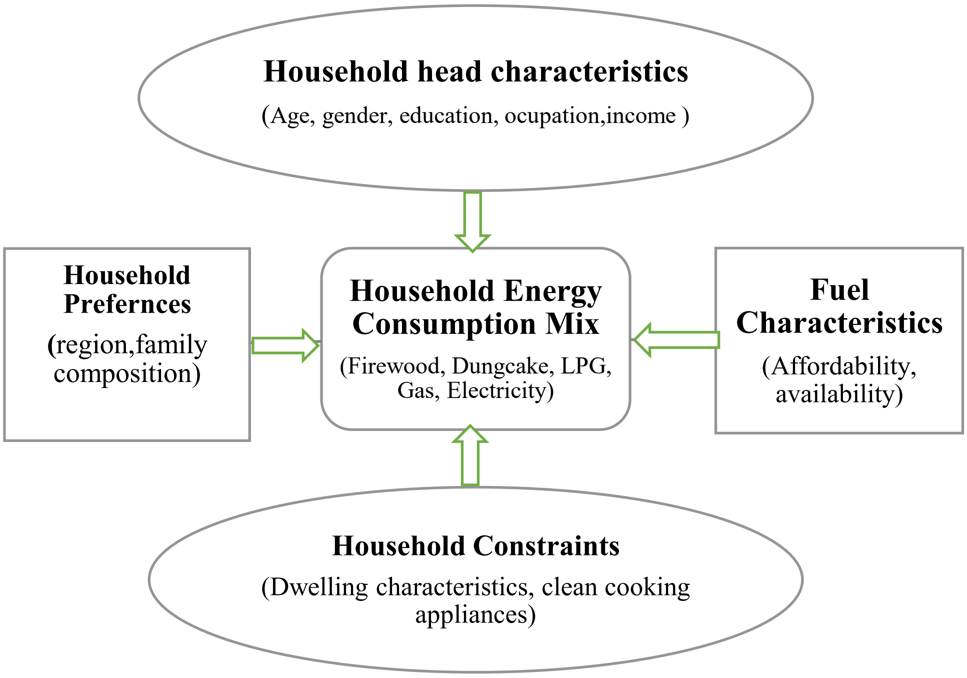
In contrast to the energy ladder, the energy mix model offers a more comprehensive understanding of household energy decisions, acknowledging that these choices are shaped by a variety of interconnected factors. This entails the persistent utilization of fuels commonly referred to as "inferior" for purposes. According to the energy mix model, households select fuels according to their energy requirements and financial resources, resulting in a varied combination that is influenced by external factors. The model's flexibility enables it to consider multiple factors influencing household energy consumption, resulting in a more comprehensive and pragmatic comprehension of the intricacies involved.

Even though many households are shifting to modern energy sources, a lot of families still hold on to traditional fuels. This is largely because of cultural habits passed down through generations, limited awareness about cleaner options, and the availability of cheap, easy-to-find resources like dung, waste, and fodder. These factors make it hard for families to completely switch to modern fuels, leading them to rely on a mix of both old and new sources—what we call fuel stacking. Cultural traditions and the lack of knowledge about better alternatives play a huge role in why many people continue to use traditional fuels, even when cleaner options are available (Hassam et al., 2021).

The composition of a household's energy mix is shaped by two main factors: the household's internal characteristics and external factors related to the available fuels. Internal factors include household head characteristics such as age, gender, education, occupation, and income, which influence energy consumption patterns. Additionally, household preferences, such as region and family composition, play a significant role in determining the types of fuels used. On the external side, fuel characteristics, including affordability and availability, heavily influence the choice of energy sources. Furthermore, household constraints, like dwelling characteristics and access to clean cooking appliances, also impact energy choices.

These internal and external factors interact to create a unique and dynamic energy mix, demonstrating the complex relationship between individual household dynamics and the broader fuel landscape, as illustrated in Figure 0.2.,

Figure 0.2: Conceptual framework adapted from chambwera & folmer(2006) and modified for Energy mix consumption



3.3 Theoretical Framework

3.1.1 Utility Maximization Problem

Demand systems prioritize utility, which refers to the satisfaction of consuming goods and services. Consumers aim to maximize utility by choosing the most desirable goods and services within their budget. A utility function that meets certain axioms, such as completeness, transitivity, and reflexivity, can model consumer decision-making. The axioms above ensure that the utility function accurately reflects consumer preferences and choices (Deaton & Measurer, 1998a; Varian, 1992).

$$U = f(x_i)$$

The utility is a function of x, where x is a vector of quantities of different cooking fuels subject to a budget constraint

$$u = (x_F, x_D, x_{Lpg}, x_{gas}) \qquad (3.2.1)$$

Where,

$x_F = firewood\ consumption$

$x_D = dungcake\ consumption$

$x_{Lpg} = LPG\ consumption$

x_{gas}= Natural Gas consumption

The consumer can choose among these cooking fuels, subject to a budget constraint.

$$\sum_{i=1}^{n} p_i\, x_i \ \leq M \qquad (3.2.2)$$

Where,

p_i= prices of i^{th} cooking fuel

x_i = quantity demanded of i^{th} cooking fuel

M= is the available budget for purchasing i^{th} cooking fuel

The Lagrangian framework is used to solve optimization problems subject to constraints. In the case of utility maximization subject to a budget constraint,

$$\mathcal{L} = \ u\left(x_F, x_D, x_{Lpg}, x_{gas}\right) + \lambda(\ M - \sum_{i=1}^{n} p_i\, x_i \ ) \qquad (3.2.3)$$

When the marginal utility of income, represented by the Lagrange multiplier λ, is equal to zero, it indicates that the budget constraint is not binding—if the Lagrangian function $\mathcal{L}$ is twice differentiable concerning i^{th} quantity and λ, setting the derivatives equal to zero yields the first-order necessary conditions for local maximization.

$$\frac{\partial \mathcal{L}}{\partial x_i} = \frac{\partial u}{\partial x_i} - \lambda p_i = 0 \qquad \forall i = 1, \ldots\ldots, n \qquad (3.2.4)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = M - \sum_{i=1}^{n} p_i\, x_i \ \ = 0 \qquad (3.2.5)$$

The simultaneous solution of the 3.2.4 and 3.2.5 equations gives the Marshallian demand equation.

$$x_i = \ m_i\ (M, p) \qquad (3.2.6)$$

It represents the uncompensated (or Marshallian) demand function for the i^{th} good. This function indicates the quantity of the fuel demanded by a consumer as a function of the consumer's income *M* and the prices of goods in the market *p*.

From equation 3.2.3,

$$\frac{\partial u}{\partial x_i} = \lambda p_i \tag{3.2.7}$$

Solving for λ gives

$$\lambda = \frac{\frac{\partial u}{\partial x_i}}{p_i} \qquad \forall i = 1, \ldots\ldots, n \tag{3.2.8}$$

It results in a marginal rate of substitution

$$MRS_{ij} = \frac{\frac{\partial u}{\partial x_i}}{\frac{\partial u}{\partial x_j}} = \frac{p_j}{p_i} \qquad \forall i \neq j \tag{3.2.9}$$

It indicates that the price ratio equals a marginal rate of substitution of cooking fuels at the market rate. The indirect utility function can be obtained by substitution of the Marshallian demand function into the direct utility function, i.e.,

$$U = f(x_i)$$

$$u^* = u(m_i\,(M, p)) = v = v(P, M) \tag{3.2.10}$$

It indicates that the prices and income are directly related to utility. This solution of primal optimization is an indirect utility function.

The framework of the utility maximization function under budget constraint can be used to derive demand elasticity, which can be expressed as the ratio of the percentage change in the quantity purchased to the percentage change in the prices. The three basic demand elasticities are ownership, cross-price, and income elasticities.

3.1.2 Expenditure Minimization Problem:

The concept of duality, first proposed by Hotelling in 1932 and subsequently enhanced by Shepard in 1953, presents a valuable conceptual framework for examining consumer behavior and improving decision-making processes. Within this conceptual framework, the objective of the consumer to optimize utility is redefined as the endeavor to minimize the financial resources necessary to attain a specific degree of contentment. Adopting this dual perspective provides a deeper understanding of the relationship between maximising utility and minimising costs.

Minimize $p_i\, x_i = M$ (3.2.11)

Subject to $U = f(x_i) = \left(x_F, x_D, x_{Lpg}, x_{gas}\right)$ (3.2.12)

This problem can be addressed by establishing the Lagrangian function and evaluating the system of first-order conditions, which yield the compensated or Hicksian demand functions.

$$x_i = h_i\,(u, p) \tag{3.2.13}$$

This function u denotes the utility function of cooking fuels, prices as p, h_i represent the Hicksian demand function indicates how the quantity demanded of an ith cooking fuel at a given utility level and prices.

Substituting the Hicksian demand function into the objective function gives the expenditure cost function.

$$x = c(P, u) \tag{3.2.14}$$

The cost function (equation 3.2.14) and the indirect utility functions (equation 3.2.10) are related to each other through Roy’s identity, which enables the inversion of the indirect utility function to obtain the Marshallian demand function. Roy's identity allows us to derive the Marshallian demand function from the indirect utility function:

$$x_i = \frac{\partial v/_{\partial p_i}}{\partial v/_{\partial x_i}} = m_i \qquad \forall i = 1, \dots\dots, n \tag{3.2.15}$$

Similarly, the expenditure function (equation 3.2.14) can be inverted to Hicksian demand function by using Shepherds’ lemma:

$$x_i = \frac{\partial c}{\partial p_i} = h_i(u, p) \qquad \forall i = 1, \dots\dots, n \tag{3.2.16}$$

3.1.3 Restrictions on the consumer demand model

In microeconomic theory, analyzing the effects of parametric changes in the first-order conditions regarding prices and income involves considering constraints on the demand function. By examining the derivatives of these first-order conditions concerning prices and income, we can understand the outcomes of parametric changes (Edgerton, 1966). Four fundamental restrictions govern this analysis: adding-up, homogeneity, symmetry, and negativity. These restrictions play crucial roles in ensuring the coherence and validity of the demand system. They provide essential guidelines for empirical studies to estimate demand systems (Philips, 1974) precisely.

First, adding-up restriction on the demand function is derived from the monotonicity assumption of preferences and the budget constraint. This restriction encompasses two main types: Engel and Cournot aggregation restrictions. Second, symmetry in-demand functions are derived from consistent preferences assumed by any cost function, which is twice continuously differentiable. Young's theorem, according to Chiang (1984), asserts that under consistent preferences, the order of differentiation of the demand function concerning any two arguments does not alter the values of the derivatives. Third, the homogeneity restriction condition permits percentage changes in income and all prices. Marshallian demand functions exhibit homogeneity of degree zero in prices and expenditures, indicating that doubling all prices and income simultaneously would not alter the demands. Conversely, Hicksian demand functions are homogenous of degree zero in prices, signifying that doubling all prices while keeping income constant would not influence the demands. This property reflects the absence of money illusion. Lastly, Negativity Restriction implies that compensated price responses of the (n*n) matrix, also known as the substitution or Slutsky matrix, are characterized by harmful elements and semi-definiteness. The Slutsky matrix is negative, and the concavity of the cost function implies semi-definite. Specifically, all elements on the diagonal of the substitution matrix are harmful, following the necessary condition for negativity.

This implies that, while holding utility constant, if the price of a good changes, the demand for that good must either decrease or remain unchanged. This observation aligns with the law of demand, which states that there is an inverse relationship between the price of a good and the quantity demanded, all else being equal. Thus, the Hicksian demand functions, derived from the Slutsky matrix and reflect how consumers adjust their consumption in response to price changes while keeping utility constant, are closely related to the law of demand. They illustrate how price changes influence consumer behavior, contributing to our understanding of market dynamics.

3.1.4 Demand system selection criteria:

Prioritize theoretical consistency when selecting a specific demand function for empirical study. Furthermore, Diewert (1974) and Lau (1986) emphasized that the chosen functional form should balance simplicity and flexibility. For empirical analysis, the estimated preferences function should be sufficiently flexible without imposing constraints on its free parameters. This ensures we can approximate the second order, twice-continuously differentiable preference function (Diewert, 1971). In contrast, limiting the number of parameters and using a linear functional form can increase the degree of freedom in the estimation procedure, promoting simplicity. Furthermore, the chosen functional form should reflect the complementary or substitution relationships between goods. This capability enables the description of demand for necessities, inferior goods, and luxury items, providing insights into consumer behavior and market dynamics.

Demand systems can be classified into three subgroups: Directly Specified Demand Systems encompassing demand systems like the Rotterdam System. The demand equations are explicitly specified based on economic theory or empirical observations; second, Derived Expenditure Functions or Utility derived from expenditure or utility functions, whether indirect or direct. Examples include the Linear Expenditures System (LES), where demand equations are derived from expenditure functions and other systems where demand equations are derived directly from utility functions. Third, Estimating from Flexible Functional Forms estimates demand systems using flexible, functional forms that offer versatility in capturing various demand patterns. Examples include the Indirect Translog System (ITS) and The Almost Ideal Demand System (AIDS), which allow for a more nuanced understanding of demand behavior without imposing rigid functional forms.

3.1.5 The Almost Ideal Demand System:

Deaton and Muellbauer (1980b) developed the Almost Ideal Demand System (AIDS), widely regarded as an effective model for estimating demand systems. The AIDS model, based on a flexible expenditure function, is simple and provides significant benefits. The model automatically satisfies aggregation requirements by imposing simple parameters like symmetry and homogeneity. This ensures that the model's predictions match aggregate consumption behavior. Furthermore, the AIDS model accurately represents nonlinear Engel curves, which improves its ability to capture real-world consumer behavior. Its functional form is also consistent with household budget data, making it ideal for empirical research into household consumption behavior. The Linear Approximate Almost Ideal Demand System (LA/AIDS), a simplified version of the AIDS model, is especially popular for empirical studies due to its simplicity and ability to capture essential aspects of demand behavior. As a result, the AIDS model has been widely adopted in empirical studies across many disciplines, including economics, agricultural economics, and consumer research.

To derive the Almost Ideal Demand System (AIDS), we start with a cost function that reflects the cost of achieving a given level of utility at given prices. Let us consider a simplified cost function:

$$c(u,p) = \sum_{i=1}^{n} p_i x_i \tag{3.2.17}$$

Where,

- $c(u,p)$ represents the cost function.
- u denotes the utility level.
- Is the price of i^{th} cooking fuel
- x_i is the quantity demanded of cooking fuel at a given utility level and price.

To derive the AIDS model, we will use the following relationship between the cost function and the Almost Ideal Demand System:

$$lnc(u,p) = a(p) + ub(p) \tag{3.2.18}$$

Where,

$lnc(u,p)$ = natural logarithm of the cost function

$a(p)$ = function of prices p, which captures the effect of prices on the cost of achieving subsistence-level utility.

$b(p)$ = the marginal cost of achieving additional utility as prices change.

The $a(p)$ and $b(p)$ are functions of prices such that their functional form is,

$$a(p) = \alpha_{\circ} + \sum_{i=1}^{n} \alpha_i \, lnp_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}{}^{*} lnp_i lnp_j \tag{3.2.19}$$

- $\alpha_{\circ}$ represents a constant parameter.
- α_i represents the elasticity of demand concerning the price of the i^{th} cooking fuel
- p_i Represents the price of the i^{th} cooking fuel.
- $\gamma_{ij}{}^{*}$ Represents a parameter capturing the interaction between the prices of the i^{th} and t^{he} cooking fuels.

The following equation represents the demand function

$$b(p) = \beta_{\circ} \prod_{i=1}^{n} p_i{}^{\beta i}$$

- $\beta_\circ$ is a constant parameter
- β_1 is the elasticity of demand concerning the price of the i[th] fuel.

  α_i,βITHnd $\gamma_{ij}{}^*$ are the parameters to be estimated.

The expenditure function represented as $lnc(u,p)$, takes the form

$$lnc(u,p) = \alpha_\circ + \sum_{i=1}^{n} \alpha_i \, lnp_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}{}^* lnp_i lnp_j + u\beta_\circ \prod_{i=1}^{n} p_i{}^{\beta i}$$

(3.2.20)

This equation describes the logarithm of the cost of achieving a given level of utility u at given prices p. The parameters α_i,$\gamma_{ij}{}^*, \beta i$ are to be estimated. Hicksian demand functions can be obtained by applying Shepherd's Lemma, which states that the derivative of the expenditure function for the price of a good gives the Hicksian demand for that good. The level of utility is dependent on total expenditures and prices is described by inverting the cost function into the indirect utility function.

The Marshallian demand function in budget share form can be derived by substituting the indirect utility function into the Hicksian demand function.

$$w_i = \alpha_i + \sum_j \gamma_{ij} \, lnp_j + \beta_i \ln\left(\frac{m}{P}\right) + u_i \qquad (3.2.21)$$

Where,

w_i = budget share of the fuel

p_j = price of j[th] fuel

α_i, β_i and γ_{ij} are the parameters to be estimated. m Is the total expenditures and P is the aggregate price index that is defined as:

$$lnP = \alpha_\circ + \sum_{i=1}^{n} \alpha_i \, lnp_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij}{}^* lnp_i lnp_j \qquad (3.2.22)$$

Where,

γ_{ij} It represents a parameter capturing the interaction between the prices of different cooking fuels, i.e.

$\gamma_{ij} = \gamma_{ji}$

It represents a symmetry property. It arises when there is a kind of interaction or exchange between two commodities. The relationship between the fuel prices is nonlinear from the above equation. Let us rewrite the relationship between fuel prices and price index using the stone price index P^* for linearisation as suggested by Deaton and Muellbauer (1980).

$$lnP^* = \sum_j w_j \, lnp_j \tag{3.2.23}$$

In the context of the Linear Approximate Almost Ideal Demand System (LA/AIDS), incorporating the Stone price index can introduce a unit of measurement error. This error arises because the Stone index violates the fundamental property of index numbers, as it varies with changes in the unit of measurement for prices.

To address this issue, a suggestion by Moschini (1995) proposes using a Laspeyres price index instead. The Laspeyres index can help correct the unit of measurement error by utilizing the sample mean for prices. The linear estimation procedure becomes simpler by replacing the Stone index with the Laspeyres index, and the measurement error associated with the Stone index can be overcome.

The Laspeyres index can be given as

$$lnP^{\mathrm{L}} = \sum_j \overline{w_j} \, lnp_j \tag{3.2.24}$$

By incorporating the Laspeyres price index into the Marshallian demand equation

$$w_i = \alpha_i + \sum_j \gamma_{ij} \, lnp_j + \beta_i \ln \left(\frac{m}{\sum_j \overline{w_j} \, lnp_j}\right) + u_i \tag{3.2.25}$$

And solving

$$w_i = \alpha^{**} + \sum_j \gamma_{ij} \, lnp_j + \beta_i \left(\ln(\mathrm{m}) - \sum_j \overline{w_j} \ln(p_j)\right) + \mu^{**} \tag{3.2.26}$$

This equation also represents budget share form, but this equation is part of the Linear Approximate Almost Ideal Demand System with the Laspeyres Price Index, where α^{**} and μ^{**} are the parameters to be estimated. It incorporates the Laspeyres price index and simplifies the estimation process compared to Stone's price index. The transition from the 3.27 to the 3.32 equation involves the incorporation of the laspyres price index to simplify the estimation process.

$$\alpha^{**} = \alpha_i - \beta_i (\alpha_\circ - \sum_j \overline{w_j} \ln(p_j) \tag{3.2.27}$$

Using the relationship proposed by Pollak and Wales (1971-1981), equation (58) is augmented with household socioeconomic characteristics as follows:

$$D_i(\eta) = \sum_{r=1}^{n} \delta_{ir}\eta_r \tag{3.2.28}$$

Where,

$D_i(\eta)$ Represents the characteristic of interest for i^{th} household, which depends on the household's socioeconomic characteristics η.

δ_{ir} = the vector of parameters.

η_r = is a matrix of socioeconomic variables.

In this study, the household characteristics (discussed in the methodology section) are incorporated into the demand function as,

$$w_i = \alpha^{***} + \sum_j \gamma_{ij}\, lnp_j + \beta_i\left(\ln(m) - \sum_j \overline{w_j} \ln(p_j)\right) + \mu^{***} \tag{3.2.29}$$

Where α^{***} incorporates the effects of household characteristics, the specific value will be calculated as,

$$\alpha^{***} = \alpha_i^{**} - \sum_{r=1}^{n} \delta_{ir}\eta_r \tag{3.2.30}$$

The adding up restriction requires that,

$$\sum_i \alpha^{***}\, 1 \text{, and } \sum_{r=1}^{n} \delta_{ir}\eta_r = 0 \qquad r = 1, \dots \dots \dots ., m \tag{3.2.31}$$

The number of demographic and other variables is represented by m.

The per capita estimation of the system of equations was conducted using Zellner's (1965) Seemingly Unrelated Regression (SUR) method. This method is especially applicable when multiple equations with correlated error terms are involved; it permits efficient parameter estimation across equations. A challenge, however, arose due to omitted observations, specifically regarding the prices of non-consumed household commodities. To tackle this concern, average prices were utilized, which enabled the inclusion of missing observations in the analysis while maintaining estimation process consistency. This methodology has been examined in prior research conducted by Wen S. Chern et al. (2003) and Cox and Wohlgenant (1986). By utilizing average prices instead of missing observations, the estimation of equations in per capita terms was made possible by applying the SUR method. By excluding a single equation and imposing theoretical conditions, it was possible to derive coefficients without compromising the estimation process of the LA/AIDS model.

3.1.6 Estimation of Demand Elasticities for LA/AIDS model:

For the LA/AIDS model, elasticity derivation is extensively investigated and well documented. Following Green and Alston (1990) and Buse (1994), concerning expenditure (m) taking the derivative of demand equation, the expenditure elasticity can be obtained as below:

$$\mathrm{e}_i = 1 + \frac{1}{w_i}\left(\frac{\partial w_i}{\partial \ln{(m)}}\right) = 1 + \left(\frac{\beta_i}{w_i}\right) \tag{3.2.32}$$

Taking the derivative w.r.t ln (p_j), the uncompensated own price elasticities (j=1) and cross-price elasticities ($j \neq i$).

$$e_{ij=-\delta_{ir}} \frac{i}{w_i}\left(\frac{\partial w_i}{\partial p_j}\right) \tag{3.2.33}$$

3.4 Study Area and Data

The present study intends to explain the situation of household carbon footprints in rural and urban regions of all the provinces, i.e., Punjab, Sindh, Khyber Pakhtunkhwa (KPK), and Baluchistan. For this purpose, this study extracted micro-level data from two rounds, i.e., 2015-16 and 2018-19 of the Household Integrated Economic Survey (HIES). The survey is the most comprehensive nationwide micro-level data set in terms of socioeconomic and demographic indicators and, in particular, illustration of consumption patterns and expenditure at national and provincial levels with rural/urban breakdown. The study used the most recent survey rounds to give a clear picture of household's carbon footprints and the changes over time.

As mentioned earlier in this chapter, the data used in this study are sourced from the Household Income and Expenditure Survey (HIES), a national-level survey conducted by Pakistan beaure of Statistics. This secondary data is pre-validated through rigorous quality control processes implemented during data collection and processing. Since HIES data is already validated and compiled according to established national standards, it does not require additional ground-truthing. Ground-truthing typically involves verifying data collected through primary methods, such as direct field observations or remote sensing, and is not applicable to survey-based secondary data like HIES. Therefore, no further field verification of the data was necessary for this study, and the absence of ground-truthing does not constitute a limitation.

The factors influencing household carbon emissions are demographic, economic, and spatial. Demographic factors regarding the household head's age and educational attainment, household gender composition, family size, and dependency ratio are used to measure the key demographic characteristics of a household as these factors combine to shape the household's experience and ability to reduce carbon emissions. The explanatory variables used in this study, along with their unit of measurement and theoretical reviews, are presented in Table 0.1.

Table 0.1. Description of Explanatory Variables

<table>
<tr><th>Variable</th><th>Description</th><th>Measurement</th><th>Previous studies</th></tr>
<tr><td>Age of Head</td><td>Age of Household head</td><td>No of Years</td><td rowspan="9">Baiocchi et al. (2010);
Büchs & Schnepf (2013);
Lin et al. (2013);
Weber & Matthews (2008);
Yang et al. (2010);
Qu et al. (2013)</td></tr>
<tr><td>Gender of Head</td><td>Female-headed households</td><td>Male=0, female=1</td></tr>
<tr><td>Household Size</td><td>Number of family members in a family</td><td>Number</td></tr>
<tr><td>Education</td><td>Schooling of household head</td><td>No years of schooling</td></tr>
<tr><td>Income</td><td>Income of household head</td><td>Rs.</td></tr>
<tr><td>Employment status</td><td>The household head is a paid employee or otherwise</td><td>Paid employee=1 otherwise=0</td></tr>
<tr><td>Marital status</td><td>Household head either married or single/divorced/widow</td><td>Married=1, otherwise=0</td></tr>
<tr><td>Household expenditure</td><td>Household Expenditure</td><td>1k Rs.</td></tr>
<tr><td>Own house</td><td>House ownership</td><td>Ownhouse=1, otherwise=0</td></tr>
<tr><td>Geographical Location</td><td>The geographical region of the house</td><td>rural=1, urban=0)</td><td>Viswanathan & Kumar (2003); Büchs & Schnepf (2013); Lin et al. (2013); Liddle (2014); Zhang & Zheng (2014); Zhang et al. (2017)</td></tr>
<tr><td>Electricity consumption</td><td>Household Consumption of electricity</td><td>KWh</td><td>Hosier & Dowd (1987); Chaudhuri & Pfa (2002);</td></tr>
</table>

Variable	Description	Measurement	Previous studies
firewood consumption	Household consumption of firewood	Kgs	Druckman & Jackson (2009); Kerkhof et al. (2009); Weber & Matthews, (2008); Sovacool & Brown (2010) Ubaidillah (2011); Cox et al. (2012)
LPG consumption	Household consumption of LPG	Ltr	
Dungcake consumption	Household consumption of dung cake	Kg	
Price of Firewood	Unit price of firewood, calculated as Expenditure / Quantity.	Rs. per Kg (Calculated)	
Price of LPG	Unit price of LPG, calculated as Expenditure / Quantity.	Rs. per Ltr (Calculated)	
Price of Dung Cake	Unit price of dung cake, calculated as Expenditure / Quantity.	Rs. per Kg (Calculated)	
Price of Firewood	Unit price of firewood, calculated as Expenditure / Quantity.	Rs. per Kg (Calculated)	

3.5 Estimation Techniques:

The following estimation techniques are employed to fulfil this study's first objective. Qu et al. (2013) defined ‘Household carbon emissions’ as direct and indirect emissions from household use and consumption. As in previous studies, household carbon emissions in this study included direct and indirect emissions. However, the difference is that we divide household carbon emissions into four parts by comparing household consumption expenditure on clothing, food, electricity, and cooking fuel. The study also helps to assess the carbon footprints for low, medium, and high consumption expenditures.

The consumption accounting perspective is critical because the production perspective shows that many Western economies are successfully reducing their carbon emissions. However, when the consumption perspective is used for accounting, not only are carbon emissions often found to be higher than compared to the production accounts, but they also tend to exhibit a rising trend (Hertwich & Peters, 2009; Minx et al., 2013; Hertwich & Peters, 2009; Minx et al., 2013). To estimate the study's first objective, the following estimation methods are used, i.e., to determine the households' direct and indirect carbon footprints.

The GHG emissions accounting of urban and rural household consumption is classified into four categories: electricity, fuel, transportation, and food consumption. GHG emissions are expressed in carbon dioxide equivalents (CO_2 eq.). GHG emissions from electricity use and fuel consumption are derived from the direct energy use of household activities such as cooking, heating, and lighting, and household appliances such as computers, televisions, and refrigerators.

3.5.1 Direct Household Carbon Footprints:

Direct carbon footprint can be seen as a carbon footprint from direct energy consumption in household activities such as household energy use for cooking, lighting, transportation, etc. In general, the Linear Multiplier Factor Method is used to estimate the direct carbon footprint of household energy consumption. First, each energy usage number is multiplied by its corresponding carbon emission coefficient or factor and then added to obtain a total direct carbon footprint for the i^{th} household. The estimation model of the direct carbon footprint of household energy consumption is expressed as follows:

$$C_i = \sum_{k}^{n} C\,F_k * A_k \qquad (3.4.1)$$

Where,

C_i= Direct carbon footprints of i^{th} household

A_k= total amount of k^{th} energy consumed

CF_k= carbon emissions factor of k^{th} energy

As the study focuses on the three primary sources of direct carbon emissions, the following equation provides an accounting framework for the empirical work. The GHG emissions from electricity use and fuel consumption are respectively calculated using the following two formulas:

$$Ee = Ec * Efe \qquad (3.4.2)$$

GHG emissions from residential electricity Ee per month is the amount of residential electricity consumption Ec per month and is multiplied by its emission factor Efe.

$$E = Fc * Efg \qquad (3.4.3)$$

Where Ef is GHG emissions from residential gas consumption per month; Fc is the amount of residential gas consumption per month; Efg is the emission factor of gas. Similarly, other energy sources like cooking fuel and private transportation are multiplied by their corresponding emission factors. The emission factors are referenced from the 2006 IPCC guidelines for national greenhouse gas inventories.

All the energy consumptions are aggregated to find the household level direct carbon emissions. This study does not address the effects of the imported goods and services consumed by urban and rural households in Pakistan. We divide the urban/ rural households into income quintiles.

3.5.2 Indirect Household Carbon Footprints

The following estimation techniques serve as the proposed methodology to estimate the objective of indirect carbon footprints. Indirect household carbon emissions include emissions embodied in food, clothing, and entertainment consumption. Owning to the lack of some goods' life cycle data for the food category in Pakistan, the formula used to calculate indirect household carbon emissions is as follows (Feng et al., 2011; Qu et al., 2013; Wei et al., 2007):

$$Eg_i = \sum Sg_i . C_g \times 10^{-3} \tag{3.4.4}$$

Where $Eg_i$is the indirect household carbon emissions, Sg_i is the consumption of g^{th} goods and services in the i^{th} household, C_g is the carbon emission factor of g^{th} goods and services.

The next step is to convert energy consumption for the representative households into carbon emissions using well-established carbon emission factors. In particular, a set of emission conversion factors from the IPCC's Emission Factors Database (EFDB) (IPCC, 2006) is used, established by the IPCC, to provide country-specific emission factors more appropriate to a local context. Indirect household carbon emissions were usually calculated by the input-output method and consumer lifestyle approach (Liu et al., 2011)(Liu et al., 2011). According to the consumer lifestyle approach, the total carbon footprints of both rural and urban areas will be estimated as

$$C = \sum i \sum t \; C_{it} = \sum i \sum t * P_i \tag{3.4.5}$$

Where C indicates the direct and indirect carbon emissions from t consumption activities by i^{-th} household. E_{ijt} denotes the per capita annual expenditure of t consumption activities by i^{th} household, while F_t refers to the carbon emission factor and P_i refers to urban household population. The same procedure is used to calculate the rural carbon footprints.

Then, we aggregate each province's rural and urban emissions to get the provincial-level estimates of household carbon emissions.

3.5.3 Construction of Variables

To investigate the determinants of household consumption expenditure and associated carbon emissions, the study extracted data on socioeconomic (household size, employment types, income, and residence types), demographic (age, education, and marital status), gender, and geographic (provincial dummies) characteristics of households and firewood consumption as a cooking fuel from 2015-16 and 2018-19 waves of HIES (PBS, 2019a), based on the existing literature.

3.5.4 Steps for carbon emissions calculations

The present study employs the conversion methodology recommended by the Intergovernmental Panel on Climate Change (IPCC) in 2018 to estimate household emissions from cooking fuel accurately. By adhering to this established scientific approach, the study ensures reliable and standardised calculations of the carbon emissions associated with household cooking fuel consumption.

To generate household firewood consumption expenditure (Y_i) variable, the study obtained firewood consumption quantities (C_i) for the ith household from HIES and multiplied with national firewood prices ($P_{firewood}$) estimated by the PBS (PBS, 2019b), which publishes monthly data of prices on a variety of energy sources including electricity, natural gas, gasoline, compressed natural gas (CNG), liquefied petroleum gas (LPG), and firewood as follows:

$$Y_i = C_i * P_{firewood} \qquad (3.4.6)$$

To construct the firewood carbon emission (E_i) variable, the study employed the Intergovernmental Panel on Climate Change (IPCC) conversion method (IPCC, 2018) to estimate firewood carbon emissions from household firewood consumption quantities (C_i) as follows:

$$\mathrm{E}f_i = C_i * \ Ce_{firewood} * Ox_{firewood} * \frac{44}{12} \qquad (3.4.7)$$

Where Ef_i represents the household carbon emissions from firewood consumption. C_i Represents the quantities of firewood consumption by the ith households. $Ce_{firewood}$ represents the carbon emission factor for firewood, $Ox_{firewood}$ is the oxidation fraction of carbon that is wholly oxidized during combustion, and the factor 44/12 is used to convert the resulting carbon emissions into carbon equivalent.

The methodology mentioned above is utilized for quantifying emissions from various cooking fuels, including non-renewable sources such as LPG, kerosene oil, and coal, as well as biomass fuels like firewood and dung cakes. This comprehensive approach allows for a comprehensive assessment of carbon emissions across a range of commonly used cooking fuel types. Table 3.2 presents the emission factors utilized in the calculation of carbon emissions.

$$Elpg_i = C_i * Ce_{lpg} * Ox_{lpg} * \frac{44}{12} \tag{3.4.8}$$

$$Ekerosene_i = C_i * Ce_{kerosene} * Ox_{kerosene} * \frac{44}{12} \tag{3.4.9}$$

$$Ecoal_i = C_i * Ce_{coal} * Ox_{coal} * \frac{44}{12} \tag{3.4.10}$$

$$Edungcake_i = C_i * Ce_{dungcake} * Ox_{dungcake} * \frac{44}{12} \tag{3.4.11}$$

Table 0.2: Emission factors for Cooking Fuels

Cooking fuels	Emission factor (kg Co_2 /kg fuel)
Firewood	30.5
Dung Cake	28.46
Liquefied Petroleum Gas	17.2
Kerosene oil	19.6
Coal	25.75

Source: IPCC

3.6 Determinants of Household's Carbon Footprints:

The objective for estimating the critical determinants of household carbon footprints would help to understand the factors responsible for household carbon emissions, which is essential to take effective mitigation measures (Honjo & Fujii, 2013). To solve this problem, scholars have studied the relationship between household carbon emissions and multiple household characteristics using ordinary least squares (OLS) from several different countries (Baiocchi et al., 2010; Büchs & Schnepf, 2013; Brand et al., 2013). While the OLS regression method significantly contributes to determining the major factors that influence each household's carbon emissions, there are still two shortcomings in mitigation policies.

In the first place, the OLS regression method, as a form of mean reversion, views the effects of each household trait as the same concerning carbon emissions from all households. However, it seems pretty doubtful that high-carbon households and low-carbon households are equally prone to changes in household characteristics. Second, the OLS regression method cannot demonstrate the size of the contribution of household characteristics to the variations in household carbon emissions. The present research is inspired by previous studies to revisit the subject using the Heckman selection method to investigate how household characteristics influence household carbon emissions. To assess the possible determinants of carbon emissions, several characteristics are included as the household's socio-demographic, economic and local features.

3.6.1 Heckman Selection Model

To investigate the socioeconomic, demographic, and geographic determinants of household consumption, the HIES data was used as mentioned above. The HIES data on cooking fuel consumption indicate that various cooking fuels are used for cooking and heating purposes out of 24,809 households. This indicates that consumption data must include households due to natural exclusion restrictions. However, the Heckman selection model can correct for this selection bias and provide unbiased estimates, even when there are substantial missing observations (Heckman, 1976; Koné *et al.,* 2019). The Heckman method involves two stages. In the first stage, a selection model is estimated to identify the factors affecting the likelihood of fuel type adoption in the sample, given a set of independent and firewood exclusion restriction variables. The predicted probabilities from the selection model are then used as an additional regressor in the second stage to control sample selection bias. The selection stage model is given as follows:

$$F_i = \alpha X_i + \beta Z_i + \varepsilon_i \qquad (3.5.1)$$

Where F_i represents the dichotomous fuel energy choice variable, where a value of '1" indicates that the ith household chooses firewood as the cooking fuel, otherwise '0'. X_i represents a vector of socioeconomic, demographic, and geographic characteristics of the surveyed households, such as household head's age, gender, education, marital status, occupation, income, household size, dwelling types, and geographic characteristics such as region and province. The variable Z_i serves as the vector of exclusion restrictions for fuel type consumption, indicating whether the ith household has access to firewood for cooking, measured by ownership of a clean cooking stove and cooking range. α and β are vectors of their respective coefficients. ε is a random error term.

In the second stage of the Heckman selection model, we investigate the socioeconomic, demographic, and geographic determinants of fuel energy consumption expenditure (Y_i) of the ith household as follows:

$$Y_i = \alpha X_i + \gamma \hat{F}_i + \mu_i \qquad (3.5.2)$$

Where Fi represents the predicted probabilities of the firewood energy choice variable for the ith household from the selection stage model, and γ is its coefficient. μ is a random error term. Moreover, the inverse mills ratio obtained from the selection equation is as follows:

$$\lambda_i(y_i) = \lambda_i\,(-x_i - z_i * \beta/\sigma_v) \qquad (3.5.3)$$

3.6.2 Tobit Regression Method

To identify household's socioeconomic, demographic, and geographic factors driving carbon footprints from firewood consumption, first, we quantify household consumption quantities from household fuel expenditure; and then, we estimate carbon emissions resulting from household fuel consumption using the well-established carbon emission factors obtained from the Intergovernmental Panel on Climate Change (IPCC) Emission Factors Database (EFDB) (IPCC, 2018). Then, the Tobit regression method was employed as the amount of carbon emissions (E_i) by the ith household is represented by the latent variable E_i^*. The data is assumed to follow a normal distribution with a mean and standard deviation. E_i^* cannot be directly observed. Instead, we observe the censored values of E_i, which is defined as:

$$\mathrm{E}_i = max(E_i^*, c) \qquad (3.5.4)$$

The censoring threshold is represented by c, which is the least firewood emissions a household must create to be included in the sample. The Tobit regression equation for estimating the relationship between firewood emissions and household characteristics is given below:

$$\mathrm{E}_i = \alpha_0 + \alpha_1 X_i + \sigma_i \qquad (3.5.5)$$

Where E_i represents the carbon emissions estimated from each household's firewood consumption. X_i represents a vector of the household's socioeconomic, demographic, and geographic factors. α_0 is an intercept. α_1 represents a vector of coefficients for each independent variable. σ Represents the error term.

3.7 Spatial Patterns of Household Emissions:

The study used Geographic Information System (GIS) technology, especially the ArcGIS application, to analyze the geographical patterns of residential emissions. GIS is a powerful tool for integrating, visualizing, and analyzing geospatial data, allowing us to investigate the geographical distribution and trends of home emissions across Pakistan. The following steps were engaged in the technique for this geographical analysis:

The statistics on household consumption expenditures are from the 2018-19 Household Integrated Economic Survey (HIES). The survey gave helpful information on the purchasing habits of Pakistani households in various locations. To quantify the environmental effect of household spending, we used well-established emissions factors to translate expenditure data into carbon emissions. Emissions factors are standard conversion factors that link the use of various commodities and services to the carbon emissions associated with them. We could estimate the carbon emissions associated with various products and services purchased by families by applying these emissions factors to household consumption expenditure data.

Using this method, the carbon footprints of household consumption acquire insights into the environmental consequences of household spending habits. Our study is based on solid and well-known procedures that use proven emissions variables, assuring the results' trustworthiness and credibility. Converting household consumer expenditure to carbon emissions is critical for understanding households' contribution to overall carbon emissions in Pakistan. It gives valuable information to policymakers. We used geocoding to visualize the emissions data on a map, adding geographical coordinates (latitude and longitude) to each household's emissions data. This enabled us visualize the emissions data on the map to identify and visualize the emissions data on the map precisely. We combined additional relevant geospatial variables, such as administrative borders, land use, population density, and household emissions data, to contextualise the emissions trends within a larger geographical framework.

We used ArcGIS to get the spatial patterns on the geocoded emissions data and integrated datasets. These emissions analyzes used spatial autocorrelation, hotspot analysis, and spatial interpolation approaches to detect household emissions' clusters, trends, and geographical distribution patterns. We generated themed maps to graphically portray the spatial patterns of home emissions using the findings of the spatial study. Using the maps, we identified places with high emissions concentrations, areas of possible environmental concern, and differences in emissions across provinces.

We assessed the geographical analysis and findings, gaining insight into the underlying factors driving emission patterns, such as population density, socioeconomic features, and availability of cleaner cooking technology. These interpretations helped us understand the geographical patterns of household emissions and their possible environmental consequences.

3.8 Mitigation Measures:

As discussed in the proposed research, households significantly contribute to GHG emissions. Households have been targeted in the research for appropriate carbon reduction measures (Streimikiene & Volochovic, 2011).

The carbon reduction measures already discussed in the literature are based on the demand and supply side. However, measures for carbon abatement are proposed at the consumer levels based on the research results of this study to fulfil the objective of exploration mitigation measures at the provincial and national levels for households.

Chapter 4

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

The study utilized datasets of two Household Income and Expenditure Survey (HIES) rounds, namely HIES 2015-16 and HIES 2018-19. The HIES 2015-16 dataset comprised a total of 24,238 households. Among these households, approximately 33% were classified as rural, while approximately 67% were categorized as urban, reflecting the distribution of households across different regions. The dataset revealed distinct subsections of household information, such as energy usage. Specifically, 2,947 households were using LPG, 749 households were relying on kerosene, 7,873 were using firewood, and 3,314 were using dung cakes. The selection of this sub-sample was based on positive energy consumption expenditures. The statistical summary in Table 4.1 provides information on household characteristics, types of cooking fuels as well as their associated expenditures, and carbon emissions. These values are derived from the HIES 2015-16 dataset.

Table 4.1. Descriptive Statistics of Variables (HIES 2015-16)

Variables	Mean	Std. Dev.	Min	Max
Household head age (years)	46.16	13.16	11	99
Household head education (years)	9.17	3.68	0	16
Income (Rs/year)	428996	728739	5000	3.94E+07
Per capita income (Rs/year)	78113	128004	2203	5628572
Household size (No.)	6.50	3.24	1	63
Household firewood expenditure (Rs/month)	15555.0	13001.4	720	312000
Household firewood consumption (Kg/month)	25.9	21.7	1.2	519.6
Household firewood carbon emissions (Gg/month)	42.6	35.6	2.0	854.1
Household dung cake expenditure (Rs/month)	7703.5	9919.6	240	360000
Household dung cake consumption (Kg/month)	59.9	77.1	1.9	2797.2
Household dung cake carbon emissions (Gg/month)	178.9	230.3	5.6	8358.6
Household LPG expenditure (Rs/Ltr)	12585.44	10231	600	180000
Household LPG consumption (Kg/month)	10.64	8.65	0.50	152.1941
Household LPG carbon emissions (Gg/month)	27.90	22.6	1.33	399.
Household Natural Gas expenditure (Rs/month)	7703.45	9919.57	240	360000
Household Natural Gas emissions (Kg/month)	59.86	77.08	1.86	2797.20
Household Natural Gas carbon emissions (Gg/month)	178.86	230.32	5.57	8358.65

Source: Estimated using 2015-16 HIES data.

The HIES 2018-19 survey encompassed a larger sample size of 24,807 households. In this survey, approximately 65% of the households represented the rural population, while the remaining 35% represented the urban population. Within this dataset, specific sub-populations were identified, including 9,142 households using gas, 3,865 households using LPG, 341 households using kerosene, 331 households using coal, 10,636 households using firewood, and 4,328 households using dung cakes. Similar to the previous dataset, these sub-populations were selected based on positive consumption expenditures, as shown in Table 4.2.

Table 4.2. Descriptive Statistics of Variables (HIES 2018-19)

Variable	No of obs.	Mean	Std. Dev.	Min	Max
Household head age (years)	24,809	45.84	13.61	16	99
Household head education (years)	24,809	8.40	3.93	0	18
Income (Rs/year)	24,809	341,835	392,421	0	18,000,000
Household size (No.)	24,809	6.45	3.23	1	55
Household firewood expenditure (Rs/month)	10,636	104.5	192.5	0	4000
Household firewood consumption (Kg per capita /month)	10,636	23.97	21.2	0	400
Household firewood carbon emissions (kg per capita/month)	10,636	11.29	10.04	0	473
Household dung cake expenditure (Rs/month)	4,328	16.46	55.2	0	3000
Household dung cake consumption (Kg per capita /month)	4,328	15.87	17.9	0.3	600
Household dung cake carbon emissions (kg per capita/month)	4,328	30.3	10.5	0	657
Household LPG expenditure (Rs/11 Ltr)	3,865	38.7	127	0	4000
Household LPG consumption (Kg per capita/month)	3,865	1.69	1.50	0.35	30
Household LPG carbon emissions (kg per capita/month)	3,865	0.76	0.23	0	79.64

Source: Estimated using 2018-19 HIES data.

Several significant discrepancies can be seen when comparing the descriptive statistics from datasets of two separate periods, i.e., HIES 2015–16 and HIES 2018–19. The average age of household heads is 45.84 years in HIES 2018-19, while 46.16 years in HIES 2015–16, showing a reduction of average age. The average education by household heads also varies, from 9.17 years in HIES 2015–16 to 8.40 years in HIES 2018–19. This basic comparison illustrates variations in average values across different years.

These findings from the two datasets, as shown in Table 4.1and Table 4.2, provide valuable insights ito the distribution of households across different regions and the prevalence of various cooking fuel sources, such as LPG, kerosene, firewood, and dung cakes. These datasets are fundamental for analyzing and understanding household energy consumption patterns and their implications for sustainable energy planning and policy-making. The household sector is a significant area for national climate mitigation efforts, typically accounting for approximately 19 percent of the country's total greenhouse gas (GHG) emissions (UNFCCC, 2024; Ministry of Climate Change, 2023). This study establishes its significance by focusing on a select portion of this high-impact sector. Based on the calculated coverage and demographic representation of the sample, the project's scope is estimated to address 10 to 12 percent of the total emissions attributed to the national household sector . This focus, therefore, corresponds to an overall analysis of 1.9 to 2.3 percent of the total national emissions , providing a highly relevant and quantifiable basis for developing targeted, evidence-based mitigation strategies within the broader national climate agenda.

4.1.1 Household Food Consumption and Emissions:

4.1.1.1 Household food emissions:

To comprehend the environmental consequences of food consumption, it is necessary to consider the emission of greenhouse gases (GHG), particularly carbon emissions. The present study used the HIES 2018-19 data to explain the consumption and emissions of households in rural and urban regions of Pakistan. The carbon emissions factors for various food items are presented in Table 4.3.

Table 4.3. Carbon Emission Factors of Food Items

Food item	**Carbon Emission Factor CO_2**	**Global Warming Potential (CO_2 eq)**
Grains		
Wheat	45.00	118.56
Rice	75.00	1221.23
Pulses	83.30	306.79
Dairy /Meat		
Milk	30.0	730.00
Eggs	1.00	587.54
Poultry	50.00	846.00
Mutton	65.00	12062
Vegetables		
Leafy vegetables	13.3	28.12
Other vegetables	12.5	31.12
Fruits		
Apple	41.7	330.54
Banana	10.0	71.6

Source: IPCC carbon emission factors (2016)

There are four main stages of food production to consumption: production, processing, transportation, and final preparation. The current study made use of predetermined final product consumption. The food mentioned above items' consumption amounts in kilograms and litres are used to estimate emissions. Table4.4 depicts the descriptive of household emissions of various raw food items :

Table4.4. Descriptive of Household food items' carbon emissions (kgs per month carbon equivalent)

Variable	Mean	Std. Dev.	Min	Max
Wheat	235.3	147.60	5.37	3226.5
Rice	681.57	832.27	22.8	14655.6
Pulses	19.84	13.18	2.55	255.56
Milk	442.79	316.50	5.32	4769.55
Eggs	74.89118	67.87	5.88	1412.16
Poultry	59.59	39.23	4.23	634.5
Mutton	1088.08	1043.93	62.7	15680.6
Leafy vegetables	0.513	0.29	0.04	3.75
Other vegetables	0.70	0.50	0.10	10.89
Apple	24.02	17.25	2.76	442.22
Banana	15.28	10.20	0.716	412.41

Source: estimated using HIES 2018-19

Wheat, on average, emits 235.3 units of CO_2, with emissions ranging from 5.37 units to 3226.5 units. Rice consumption, with a typical consumption of 681.57 kgs, contributes to more significant emissions. Despite their minor emissions, pulses have a measurable influence, with an average of 19.84 units. Mutton has the most significant emissions of any animal-based product, with an average of 1088.08. Emissions from poultry and eggs are also present, albeit lower. Vegetables like leafy greens and other vegetables have substantially lower emissions, with averages of 0.513 and 0.70 units, respectively. Fruits like apples and bananas emit fewer CO_2 emissions than meat and cereals. The previous studies also depict that meat and meat-related items emit higher carbon emissions (Hyland et al., 2017; Sonesson et al., 2009).

Table 4.5: Household Emissions for food groups (tons per capita per month carbon equivalent)

Food groups	Mean	Std. Dev.	Min	Max
Cereals	0.152	0.110	0.015	0.125
Pulses	0.029	0.013	0.0025	0.255
Dairy	0.077	0.05	0.0016	0.596
Meat	0.177	919	105	1576
vegetables	0.015	0.62	0.19	11.37
Fruits	0.041	0.023	0.004	0.67

The given emissions provide insightful information on how different food groups affect the environment. With the highest mean emissions of 0.17 tons per capita per month among the dietary categories analyzed, meat significantly impacts environmental degradation. With a mean consumption of 0.07 tons per capita per month, dairy products also show significant emissions, highlighting the significance of incorporating sustainable methods into dairy production and processing. Cereals and pulses, on the other hand, had mean consumption levels of 0.152 and 0.029 tons per capita per month, respectively, indicating comparatively lower emissions. This emphasizes how critical it is to use focused mitigation techniques to reduce the environmental impact of meat production and consumption.

4.1.2 Household Cooking Fuels Consumption and Emissions:

Based on the outcomes of the descriptive analysis, it is apparent that households exhibited a diverse range of preferences when it comes to fuels for domestic purposes. The quantified data in

Table 4.6 reveals the average monthly magnitude of non-renewable energy consumption expenditure per capita.

These findings indicate that households made use of multiple non-renewable and biomass options. Firewood was the most extensively consumed fuel, followed by dung cake, coal, LPG, and kerosene. These results align with a previous study by Baul et al. (2018), which observed a comparable pattern in Bangladesh, with firewood exhibiting the highest consumption magnitude at 160.14 kg per household per month.

Table 4.6. Magnitude of Cooking Fuel Consumption expenditure(Rs/month) in Households in 2018-19

Provinces	LPG	Natural gas	Firewood	Dung cake
KPK	64.03	47.8	42.74	12.89
Punjab	45.69	40.43	23.68	21.77
Sindh	3.76	39.7	14.60	12.61
Balochistan	47.83	35.53	33.58	6.72
Total	38.7	41.14	27.38	16.4

Source: Estimates using 2018-19 HIES data

The magnitudes of carbon emissions to the findings about the carbon emissions of cooking fuels are shown in Table 4.7. This table provides a detailed summary of the magnitude of monthly cooking fuel emissions in households in different provinces for the fiscal year 2018-

19. The emissions are expressed in carbon equivalent per month and provide information on the contributions of different fuel sources.

Using firewood leads to 51.95 kgs of emissions from solid fuels. Burning dung cake, with a yearly emission rate of 30.3 kgs, is the province’s biggest source of emissions. It is significant to note that these numbers represent the environmental impact of the national energy use. LPG, natural gas, kerosene oil, firewood and dung cake emissions all add to the area’s overall carbon footprint and level of air pollution. Reduced reliance on high-emission fuels and the promotion of cleaner energy sources can assist in lessening the adverse effects on the environment and advance sustainable development. Annual emissions from various energy sources show diverse trends in the Punjab province.

Emissions from various cooking fuel sources across all provinces reveal considerable disparities in their relative contributions. LPG, natural gas, kerosene oil, firewood and dung cake emissions contribute to the province's carbon footprint and air pollution. Encouraging cleaner energy options and advocating for sustainable practices can be critical in reducing environmental impacts and building a greener and better living environment. These findings emphasize the necessity of using cleaner, more sustainable cooking fuels to minimize total carbon emissions and the environmental effect of household cooking practices.

Table 4.7. The magnitude of monthly Cooking Fuel emissions (kg CO_2 eq/ fuel) in Households in 2018-19

Provinces	LPG	Natural gas	Firewood	Dung cake
KPK	1.16	7.2	20.5	23.3
Punjab	0.85	6.6	93.9	40.1
Sindh	0.06	6.05	79.4	23.3
Balochistan	0.87	5.41	14.0	13.3
Total	0.70	6.27	51.95	30.3

Source: Estimated using 2018-19 HIES data

4.2 Econometric Analysis Household Cooking Fuel Consumption and Emissions

4.2.1 Firewood consumption and emissions

4.2.1.1 Household Firewood Consumption and its Determinants

To anticipate the determinants of household firewood consumption, this study used the Heckman selection model, as all households are not using firewood energy for cooking due to natural exclusion restrictions. The results of the first and second stages of the Heckman selection model are reported in columns 2 and 3 of Table 4.8, respectively. The coefficients of explanatory variables in the first selection stage (Probit model) reflect the direction and size of their effects on the probability of having access to firewood as cooking fuel. The negative coefficient of interaction terms of female and educated household heads indicates that households are less likely to use firewood as a cooking fuel than their illiterate and male counterparts. A negative coefficient of educated females suggests that educated female heads likely yield educated females suggest that educated females. are more inclined to opt for cleaner fuel options. This inclination can be attributed to various factors.

Firstly, educated females are more likely to know about the health and environmental risks associated with traditional cooking fuels like firewood. They may have access to information about the benefits of cleaner cooking fuels and the negative impacts of indoor air pollution from solid fuels, leading them to choose cleaner alternatives. Female education is often associated with increased household empowerment and decision-making power. educated females may have more influence in household decisions, including cooking fuels, leading them to choose cleaner alternatives. Additionally, education is associated with higher socioeconomic status, affecting the affordability of cleaner cooking fuels like LPG.

Educated households may have the financial means to invest in cleaner cooking fuels and make the transition away from traditional biomass fuels more feasible with increased awareness of health and environmental issues, making educated females more likely to use Overall, the preference for cleaner cooking fuels among educated female household heads can be attributed to a combination of factors, including education, awareness, empowerment, socioeconomic status, cultural influences, and access to resources. These factors collectively contribute to a more informed and sustainable decision-making process regarding household energy choices.

These results align with earlier studies, married-educated and female-headed households prefer cleaner fuels for better health of their children and themselves (Kouser et al., 2022). This is consistent with prior research, where the education level of the household head was found to have a significant and positive impact on the choice of modern energy sources over biomass (Karimu, 2015; Rahut et al., 2017; Rahut et al.,2019; Imran & Ozcatalbas, 2020). These findings suggest that education is crucial in promoting sustainable and healthy energy practices among households.

Table 4.8. Results of Household Firewood Consumption and emissions using Heckman Selection Model and Tobit regression

Factors	**Firewood Accessibility** (Heckman first stage)	**Firewood Consumption Expenditure** (Heckman second stage)	**Firewood emission** (Tobit regression)
Household head characteristics			
Educated females	-0.462*** (0.070)	-0.187*** (0.04)	-0.77** (0.289)
Family members (Number of dependants)	0.079*** (0.005)	-0.114*** (0.003)	-0.37** (0.121)
Paid employee	-0.114*** (0.027)	-0.012 (0.017)	0.19*** (0.022)
Household and fuel characteristics			
Firewood price	-1.82*** (0.08)	-0.757*** (0.05)	-7.25*** (0.383)
LPG Price	0.098 (0.294)	3.39*** (0.179)	12.40*** (1.265)
Dung Cake	0.393*** (0.025)	0.063*** (0.017)	2.67*** (0.113)
Household Expenditure	-0.681*** (0.017)	0.017*** (0.014)	-1.59*** (0.082)
Paid firewood	9.348 (487)	-0.239*** (0.037)	-
Household geographic characteristics			
KPK	0.413*** (0.05)	0.254*** (0.030)	0.37* (0.217)
Punjab	-0.081 (0.049)	0.101*** (0.028)	-2.17*** (0.194)
Sindh	0.179*** (0.045)	-0.876*** (0.025)	-1.91*** (0.184)
Exclusion restriction variables			
Cooking range ownership	-0.028 (0.125)	-	-5.31*** (0.598)
Stove ownership	-0.182*** (0.016)	-	-6.60*** (0.115)
Constant	0.149** (0.07)	-8.82*** (0.883)	

Factors	Firewood Accessibility (Heckman first stage)	Firewood Consumption Expenditure (Heckman second stage)	Firewood emission (Tobit regression)
Model Statistics			
Observations	24,809		10636
Rho	-0.312		
Sigma	14257.18		
Pseudo Rsq			0.078

Coefficients are reported with standard errors in parentheses. *= p <0.1, ** = p <0.05, *** = p <0.0
Source: Estimated using 2018-19 HIES data.

Firewood accessibility, is positively influenced by several dependent household members, as it is a cheap energy source to meet the needs of larger households. However, in the regression analysis, the natural logarithm of the total household expenditure coefficient signifies the effect of household expenditure on the probability of using firewood as a cooking fuel. The negative coefficient of total household expenditure in the regression analysis indicating a lower probability of using firewood cooking as household expenditure increases can be explained by several factors.

Firstly, as household expenditure increases, households may have the financial capacity to afford cleaner and more convenient cooking fuels such as LPG and electricity. secondly, households with more financial resources may prioritize convenience, cleanliness and safety when choosing a cooking fuel. Higher household expenditure may be associated with higher levels of education and awareness about the health and environmental impacts of using firewood as cooking fuel. They may choose to invest in cleaner alternatives for the well-being of household family members. This suggests that households with higher expenditure levels are less likely to use firewood for cooking. Conversely, lower total expenditure is associated with a higher likelihood of using firewood, possibly due to financial constraints or limited access to alternative fuel sources.

This is consistent with the study of (Biran et al., 2004), which explains that households start demanding cleaner energy with higher income. This insight underscores the socioeconomic dynamics influencing fuel choice patterns. It highlights the importance of considering household expenditure levels in energy access and policy interventions promoting cleaner cooking fuels. The households in KPK use more firewood than those in Balochistan. These differences in fuel choice might stem from various factors, like cultural preferences, local availability of firewood or specific economic conditions prevailing in each region. At the same time, households in Punjab are less inclined to depend on firewood than in Balochistan.

The availability and urbanisation could influence this trend; access to alternative fuels and variation in cooking practices are prominent in the region, and households in Sindh use more firewood than those in Balochistan. The fuel choices among households in different regions of Pakistan vary significantly,These differences in fuel preference can be attributed to a combination of factors, including cultural preferences, the local availability of firewood, and specific economic conditions prevailing in each region. Cultural traditions and practices play a significant role in determining fuel choices, with regions having distinct norms and preferences regarding cooking methods and fuel types.

Additionally, the availability of firewood as a fuel source varies across regions, with areas abundant in firewood likely to have higher reliance on it for cooking. Economic factors, such as income levels and affordability of alternative fuels, also influence fuel choices, with regions with lower economic prosperity opting for cheaper fuel sources like firewood. Furthermore, urbanization and access to alternative fuels play a role, as urban areas tend to have better access to cleaner fuel options, leading to lower dependence on firewood in regions with higher urbanization rates like Punjab.

Variations in cooking practices, environmental awareness, and infrastructure development for distributing alternative fuels are additional factors that contribute to the differences in fuel choices among households in different regions of Pakistan, highlighting the complex interplay of cultural, economic, and environmental factors shaping fuel preferences. This finding is aligned with previous research conducted by Rahut et al. (2020) investigating the preferences for cooking fuel in different regions of Pakistan.

Among exclusion restriction variables, ownership of a cooking range and clean cookstoves decreases the likelihood of firewood accessibility. Notably, exclusion variables in the selection equation reveal a negative association between cooking appliances and firewood. The negative correlation between the adoption of modern cooking technologies, such as cooking ranges and clean cookstoves, and the availability of firewood can be explained by several factors. Firstly, these appliances typically utilize alternative fuels like natural gas, electricity, or LPG, known for their efficiency, cleanliness, and reduced environmental impact compared to traditional biomass fuels such as firewood.

Secondly, owning such appliances signifies a certain socio-economic status and access to infrastructure, making it easier to access cleaner fuel sources and modern energy services, thus reducing dependence on firewood. The inconsistency of using firewood alongside modern cooking appliances also contributes to this negative relationship. Modern cookstoves and cooking ranges are designed to work best with specific fuel types, making firewood impractical and potentially inefficient. As a result, households with modern cooking appliances are more likely to use fuels compatible with their equipment, such as natural gas or electricity, rather than firewood. Research conducted in Pakistan and India by Hasan and Zhang (2018) and Kulkarni et al. (2022) has underscored a shift towards cleaner cooking technologies, emphasizing the significance of advocating for modern cooking appliances and cleaner fuel alternatives to mitigate indoor air pollution, enhance health outcomes, and address environmental degradation associated with traditional biomass fuel consumption.

In the model, several variables, such as the logarithm of fuel prices, play a crucial role in shaping household fuel choices. The negative coefficients of firewood and dung cake prices indicate that households are less likely to use firewood as these fuels increase. The negative coefficients associated with firewood and dung cake prices in the model imply that as the prices of these traditional biomass fuels increase, households are less inclined to use them for cooking. This can be attributed to higher prices rendering firewood and dung cakes less economically viable options for households, prompting them to explore alternative fuels. Conversely, the positive coefficient for the logarithm of LPG prices suggests that as LPG prices rise, households are more likely to turn to firewood for cooking.

This phenomenon can be explained by affordability considerations - as the cost of LPG escalates, households may opt for cheaper alternatives like firewood to fulfil their cooking requirements. The results highlight the intricate relationship between socioeconomic, demographic and cultural factors as determining factors for household firewood as cooking fuel preferences. Fuel price and regional characteristics emerge as crucial determinants, reflecting the diverse influence shaping households' choices regarding firewood as cooking fuel.

The coefficients of explanatory variables for the second stage of the Heckman model for household consumption expenditure are presented in the 3rd column of Table 4.8. The negative coefficient for educated female-headed household heads suggests that as the years of education increase among female-headed households, there is a tendency for per capita firewood consumption to decrease. This finding highlights critical factors at play. Firstly, educated individuals often have better access to information regarding different cooking fuels' health and environmental impacts. These results are consistent with Rahut et al. (2019)with the study conducted by Paudel et al. (2018). A negative coefficient suggests that households with employed heads tend to have lower per capita firewood consumption.

This finding may be due to several reasons. Firstly, employed heads have higher incomes, enabling them to afford cleaner and more efficient cooking fuels, reducing the consumption and reliance on firewood fuel. Additionally, time constraints may lead to the preference for quicker and more convenient cooking methods associated with cleaner fuels. Furthermore, employed individuals may have greater access to modern fuels or be more aware of the health benefits of clean cooking fuels. So, it indicates that employment status highlights the role of income, time constraints, and awareness in shaping household fuel use patterns.

The negative coefficient of dependent household members (number of children and elder people) suggests that as the dependant members increase, the firewood consumption decreases. As the number of children and elder members increases, families may prioritize childcare responsibilities over wood collection and usage. This shift in priority could result in reduced wood usage for cooking purposes, as females allocate more time and attention to caring for their children and elders in households and switch to efficient cooking fuels. Secondly, This could be attributed to the fact that the quantity of food cooked does not necessarily increase in direct proportion to the increase in family size. For instance, the time required and the amount of firewood needed to cook a meal may remain relatively constant regardless of whether the meal is prepared for two or three people.

Consequently, it reflects a more efficient use of resources across a large group of individuals. The negative correlation between household size and firewood consumption is in contrast with the findings of Gioda et al. (2022) for rural households in Brazil and of Ram and Bahadur (2020) in Nepal and line with the study of Nepal et al. (2011) stating that as the number of children size increases, the families chose to take care of children rather than wood collection and usage. The negative-positive association between household consumption expenditures and per capita firewood consumption expenditure aligns with the findings of Gioda et al. (2022) and Netshipise and Semenya (2022), where household firewood consumption decreases as income increases.

The coefficient for the paid source of firewood indicates that households relying on purchased firewood tend to have lower per capita consumption than those who own their firewood source. This points to several factors influencing consumption patterns: availability, accessibility, and cost considerations. Access to free or own firewood may lead to higher consumption, while purchased firewood may be used more sparingly due to additional costs. Moreover, households owning their source may be less concerned about conservation. The coefficients for logs of cooking fuel prices indicate the influence of fuel prices on per capita firewood consumption. The negative coefficient for firewood price indicates that higher firewood prices lead to reduced firewood consumption per capita, aligning with economic theory where increased prices lower demand. Conversely, the positive coefficients for LPG and dung cakes suggest that higher fuel prices increase firewood usage as households switch to more cost-effective options.

This highlights how households adjust fuel choices based on price changes to minimize costs. These findings emphasize the significant impact of fuel prices on household energy decisions, showcasing the need to consider economic factors in shaping energy transitions. Understanding price elasticity and consumer behavior are crucial for designing effective energy policies and promoting sustainable practices, especially in regions where fuel prices heavily influence fuel selection.

Similarly, the coefficients of provinces indicate that households in KPK are spending more on firewood than those in Balochistan, while households in Punjab and Sindh are spending more than those in Balochistan. This finding is aligned with a previous study by Rahut et al. (2020), which also reported higher usage of firewood for cooking in KPK households compared to other regions. This may be due to various factors, such as easy access and availability of firewood, as revealed in the study by Khan et al. (2022). Moreover, households in KPK may need more clean energy sources, such as LPG, due to underdeveloped infrastructure (Mosa *et al*., 2020).

4.2.1.2 Household Firewood Emissions and its Determinants

Determinants of household firewood emissions estimated by Tobit regression are presented in the last column of Table 4.8. The educated female The presence of educated female household heads is associated with decreased emissions from firewood. This correlation is logical and consistent, as educated female household heads are empowered to manage resources effectively. Through education and exposure to various energy sources, they are inclined to prioritize investments in cleaner energy alternatives to improve their well-being.

Consequently, educated female household heads contribute to reducing emissions from firewood by lowering its consumption. These findings are aligned with Rahut et al. (2019), who also reported that household head education has a significant role in mitigating the use of firewood for cooking. The negative and significant coefficient of paid employees suggests its antagonistic relationship with firewood emissions. The reason for this might be that employed household heads have more significant financial resources to invest in alternative cooking fuels to invest in alternative cooking fuels or technologies, contributing to invest in alternative cooking fuels or technologies, contributing to lower firewood emissions.

A positive and Significant coefficient of the number of dependants among household characteristics suggests that higher household size is associated with increased emissions. This might be because many households require more energy for cooking and heating purposes. This is in line with the findings of Paládi et al. (2014), who observed that households with joint family structures have significantly higher emissions levels than nuclear families. These differences could be attributed to various factors, including longer cooking times, greater demand for fuel, and limited access to clean energy sources. The negative coefficient of firewood indicates that as the price increases, it reduces the firewood emissions. This finding aligns with the economic theory, which suggests that demand for that product decreases as the price increases. In this context, households may opt for alternative fuels when firewood prices are high, leading to a decrease in firewood consumption and emissions. Higher prices may incentivise households to use firewood more effectively or explore energy-saving measures to mitigate costs.

The positive coefficient of LPG prices suggests that lower prices are associated with reduced firewood emissions. This result is consistent with the economic substitution effect, where households may switch from firewood to LPG as it becomes more affordable. LPG is considered a more convenient cooking fuel than firewood and is often considered a cleaner and more convenient cooking fuel for firewood, particularly regarding indoor air quality and ease of use. Therefore, lower LPG prices may encourage households to adopt LPG for cooking, reducing their reliance on firewood and associated emissions. Similarly, the positive coefficient of Dungcake indicates that lower prices for dungcake are associated with reduced firewood emissions. As dung cake is a traditional biomass fuel, it is often used as an alternative to firewood for cooking in many rural households. When dung cake prices are lower, households may use it frequently, decreasing firewood consumption and emissions. This finding supports the notion of price elasticity of demand, where changes in the price of one fuel (dung cake) may influence the demand for another firewood due to its substitutability. This finding supports the notion of price elasticity of demand, where changes in the price of one fuel (Dung Cake) influence the demand for another (firewood) due to their substitutability.

The negative coefficient indicates that higher household expenditure is associated with lower per capita emissions from firewood usage. This could be because households with higher expenditure levels can afford cleaner energy sources. These findings suggest that improving household income could positively promote the adoption of cleaner energy sources for cooking (Mislimshoeva et al., 2014). This aligns with the 7th United Nations' Sustainable Development Goal (SDG), which aims to ensure access to affordable, reliable, sustainable, and modern energy for all. Therefore, policies aimed at reducing the use of biomass fuels for cooking purposes should consider targeting low-income households and promoting income-generating activities that can improve household economic conditions.

This could be due to various factors such as increased income, improving household's access to clean energy sources or ventilation in the house. These results are consistent with prior research by Shahi et al. (2020) and Ram and Bahadur (2020), which also found a positive relationship between household size and emissions. The presence of a cooking range and clean cooking stove have negative coefficients, indicating that households owning a cooking range or stove tend to have lower per capita emissions from firewood usage. This suggests that households with modern cooking appliances may rely less on firewood for cooking.

The location of residency also impacts the household's carbonisation. Rural households significantly generate more emissions than urban households because they depend on cheaper and readily available firewood as cooking fuel. Furthermore, households in Khyber Pakhtunkhwa substantially produce more emissions than those in Balochistan, while Punjab and Sindh release fewer emissions than their counterparts in Balochistan. This finding is consistent with earlier literature (Ram & Bahadur, 2020; Shahi et al., 2020; Romanach & Frederiks, 2021; Netshipise & Semenya, 2022). The factors contributing to this trend may include limited access to clean energy sources and modern cooking technologies and a lack of awareness regarding the negative environmental and health impacts of using firewood as primary cooking fuel (Gioda et al., 2022).

4.2.2 Dung Cake Consumption and Emissions

4.2.2.1.1 Determinants of Households Dung Cake Consumption:

This study used the Heckman selection model to investigate the variables affecting household dung cake. This component is critical because it tackles the exclusionary restrictions caused by the fact that not all houses rely on dung cake for cooking. Columns 2 and 3 of Table 4.9 illustrate the outcomes of the Heckman selection model's first and second stages. This investigation employed The Heckman selection model with a two-step estimating technique. The model was applied to a dataset of 24,807 observations, 4,328 of which were chosen and 20,479 of which were not based on a sample selection criterion. Each coefficient indicates the related variable's estimated influence on the result variable. The standard error represents the degree of uncertainty associated with each coefficient estimate.

Table 4.9 Results of Household Dung Cake Consumption Using Heckman Selection Model and Tobit regression

Factors	**Dung cake Accessibility** (Heckman first stage)	**Dung cake Consumption Expenditure** (Heckman second stage)	**Dung cake emission** (Tobit regression)
Household head characteristics			
Age of head	-0.003** (0.001)	-0.005*** (0.001)	-0.041 (0.21)
Educated female head	-0.151*** (0.029)	-0.053 (0.024)	-0.77** (0.289)
Dependent family members	0.055*** (0.007)	-0.112 (0.005)	-0.37** (0.121)
Paid employee	-0.039 (0.033)	0.051 (0.030)	0.19*** (0.022)
Household and fuel characteristics			
Firewood price	0.335** (0.111)	0.545*** (0.097)	-7.25*** (0.383)
LPG Price	2.767*** (0.381)	3.390*** (0.363)	12.40*** (1.265)
Dung Cake price	0.593*** (0.037)	0.166*** (0.026)	2.67*** (0.113)
Household Expenditure	-0.144*** (0.025)	-0.063** (0.021)	-1.59*** (0.082)
Household geographic characteristics			
KPK	-0.398*** (0.072)	-0.025 (0.058)	0.37* (0.217)
Punjab	-0.058 (0.064)	0.371 (0.054)	-2.17*** (0.194)

Factors	**Dung cake Accessibility** (Heckman first stage)	**Dung cake Consumption Expenditure** (Heckman second stage)	**Dung cake emission** (Tobit regression)
Sindh	0.734*** (0.057)	0.129 (0.055)	-1.91*** (0.184)
Exclusion restriction variables			
Cooking range ownership	2.976 (0.238)		-5.31*** (0.598)
Stove ownership	-0.907*** (0.034)		-6.60*** (0.115)
Constant	10.696*** (1.933)	-13.047*** (1.800)	
Model Statistics			
Observations	24,809		4328
Rho	0.0018		-
Sigma	0.712		-
Pseudo Rsq			0.078

In the initial selection stage (Probit model), the coefficients of the explanatory variables provide insight into how they influence the likelihood of households having access to dung cake as a cooking fuel. The coefficient for head age in the selection equation suggests the relationship between the age of the household head and the likelihood of using dung cakes for cooking. Specifically, as the head's age increases, the odds of using dung cakes also decrease. This could be attributed to older individuals having less mobility or access to gather dung cake. This implies that younger heads of households are more inclined to use dung cakes than older heads. This suggests that while there may be a tendency for female-headed households to use alternative cooking methods, the evidence for this association is not strong enough to draw definitive conclusions.

An increase in education level is linked with a reduction in the likelihood of households having dung cakes, with each unit increase in education corresponding to a decrease in the odds of having dung cakes. This implies that higher education levels influence households to adopt alternative cooking methods or technologies, thereby decreasing reliance on dung cakes for cooking. These findings align with the study of Rahut et al. (2020) and Yousaf et al. (2021), which states that households with higher education are inclined to use clean energy sources.

The results indicate that paid employment is associated with a decrease in outcomes. However, this effect is not statistically significant at the conventional significance level ($p > 0.05$), suggesting that the observed difference may not be meaningful or reliable in determining the outcome variable indicating that the observed difference may not be statistically robust or significant in influencing the availability of dung cake. This may be attributed to accessibility, affordability, and cultural norms regarding dung cake consumption, as discussed in the literature (Bisu et al., 2016; Rahut et al., 2019, 2020).

The findings demonstrate that with each additional family member, there is an increase in dung cake expenditure. This relationship is statistically significant ($p < 0.05$), implying that the association between household size and dung cake expenditure is unlikely to be attributed to random chance. The positive correlation suggests that larger households tend to allocate a more significant portion of their resources towards dung cake expenditure. This observation carries several potential implications. It could imply that larger households have a higher demand or necessity for dung cake due to increased cooking or heating requirements associated with more members.

Alternatively, the result may indicate that larger households consume more dung cake for various purposes due to the presence of additional individuals. These findings shed light on the influence of household size on dung cake expenditure and provide valuable insights into households' behavior and resource allocation patterns. Among household and house characteristics, dung cake consumption is positively influenced by household size, as it is a cheaper energy source to meet the needs of larger households. Large family sizes make it easy to collect dung cake; as mentioned in a study by (Rahut et al., 2019), family labour and energy needs also increase (Pandey & Chaubal, 2011).

The positive coefficient for firewood prices suggests that as the price of firewood increases, both the accessibility and consumption expenditure on dung cake also increase. This indicates that households may use dung cake more frequently as a cheaper alternative when firewood becomes more expensive. Higher food prices could lead to seeking more affordable fuel options such as dung cake to meet their energy needs, resulting in increased accessibility and expenditure on dung cake.

Particularly, those living in the KPK region have more accessibility to dung cake than people living in other places, indicating that this energy source is more readily available in KPK. The availability of dung cake significantly in the Punjab region shows that locals have considerably more accessible access to it. The availability of dung cake has also significantly increased for Sindh inhabitants, suggesting better accessibility than other regions. These results are consistent with previous research on regional variations in energy access patterns. For instance, research has demonstrated that regional differences in the accessibility of traditional biomass fuels, such as dung cake, can be attributed to geographic location, agricultural practices, and cultural norms (Barnes et al., 2015). These findings emphasize the significance of considering regional differences in dung cake availability when formulating measures to encourage healthy cooking habits and provide fair access to renewable energy sources.

The coefficients of fuel prices represent the effects of different factors on the availability of dung cakes. Specifically, the log of firewood and LPG prices indicates that an increase in firewood prices corresponds to a higher likelihood of dung cakes being available. Additionally, an increase in dung cake prices indicates that dung availability makes dung cakes available. These findings underscore the influence of firewood, LPG, and dung availability on the presence of dung cakes as a cooking fuel option. The coefficient of log of expenditure indicates that an increase in household expenditure is associated with a decrease in the odds of having dung cakes as a cooking fuel option. However, the coefficient for owndungcake suggests that owning dung as a fuel source has no statistically significant effect on the likelihood of using dung cakes. On the other hand, the coefficient for clean cooking stoves implies that households with access to clean cooking stoves are less likely to use dung cakes, indicating a preference for cleaner and more efficient cooking methods.

The coefficients of explanatory variables for the second stage of the Heckman model are presented in the last column of Table 4.9. the negative coefficient of the head age of the household suggests that as the age of the household head decreases, the expenditure on dung cakes also decreases. In other words, younger household heads spend less on dung cakes than older ones. This could be because older individuals may have more traditional cooking practices involving dung cakes, whereas younger individuals may opt for alternative cooking methods. The positive coefficient of female heads tend to spend more on dung cakes. This could be attributed to several factors. Firstly, females are often associated with homemaking responsibilities, including cooking. In many households, females traditionally handle cooking duties and may prefer dung cakes due to their affordability and availability. Dung cakes are a cheap fuel source commonly used for cooking in many regions, making them an attractive option for households looking to save on energy expenses. Utilization.

The study emphasizes the inverse association between education and reliance on dung cake as a cooking fuel. Individuals with primary, secondary, and higher education are less likely to use dung cake, showing a greater inclination for preferring cleaner cooking fuel sources. These findings are consistent with a broader understanding that education is critical in increasing knowledge, awareness, and access to alternative energy sources. Households become more knowledgeable about the benefits of contemporary energy sources. They are more prepared to embrace and use them in their agricultural practices due to education, decreased environmental impact, and improved rural livelihoods. According to Rahut et al. (2017), research in Pakistan's Himalayan region and similar studies (Ahmar et al., 2022; Karimu, 2015; Rahut et al., 2019) show that educated households are more likely to use modern energy sources.

An augmentation in the household size by the one-unit increase is associated with an appreciable and statistically significant increase in larger households that may have more efficient cooking methods, reducing the reliance on dung cake. The cooking expenditure may remain the same with dependent household members. (Pandey et al. 2011; Bisu et al. 2016; Paudel et al. 2018).

In the context of dung cake usage, the analysis highlights the influence of geographical location. Living in rural regions, as opposed to other areas, is significantly associated with a higher likelihood of being selected for dung cake usage. This suggests that rural areas exhibit a greater prevalence of dung cake as a cooking fuel. Traditional biomass fuels are primarily used in rural regions. Previous research in Pakistan and other countries supports these findings (Aryal et al., 2019; Bakhsh et al., 2020; Hou et al., 2017).

Additionally, specific regions, such as KPK, Punjab, and Sindh, demonstrate significant associations with dung cake usage, further emphasizing regional variations in its utilization. These findings align with previous studies (Bakhsh et al., 2020; Yousaf et al., 2021). These findings shed light on the geographical factors contributing to adopting dung cake as a household cooking fuel. The province of Punjab has a lower adoption of clean cooking fuels due to the predominance of agricultural operations and the reliance on tenant-landlord interactions. In agricultural areas, fuel wood, crop byproducts, and animal dung cakes are often available, which makes them a simple and cost-effective option for cooking.

4.2.1.3 Determinants of Household’s Dung Cake Emissions:

The results of the Tobit regression analysis of household dung cake emissions are presented in the last column of Table 4.9. The household head’s variables offer insight into how age, gender dynamics and education level are connected to dung cake emissions, contributing to a deeper understanding of household environmental behaviors. The positive coefficient of the head’s age suggests a potential trend where older household heads tend to produce higher dung cake emissions, which could be attributed to traditional cooking fuel sources, cooking practices, or awareness of environmental concerns.

However, uncertainty, as indicated by the standard error, emphasizes the need for further research and perhaps more robust data to refine our understanding of the age-emission relationship. The negative coefficient suggests that female-headed households, on average, report lower dung cake emissions than male-headed households. The relatively high standard error underscores this estimate's uncertainty, emphasizing the importance of cautious interpretation. The negative coefficients of the educated heads indicate that as the household head's educational attainment increases, there is a trend of lower dung cake emissions. This suggests a potential correlation between education and adopting cleaner or more efficient cooking methods, contributing to reduced emissions.

The trends of decreasing emissions with higher education levels and the nuanced relationship between gender and emissions contribute to the discourse on sustainable household practices. However, the uncertainties of standard errors warrant further investigation for robust conclusions. These insights provide a foundation for policy formulation and interventions to foster environmentally conscious behaviors within households. The negative coefficient of the household head being a paid employee signifies that as the household income increases, their access to better and cleaner cooking sources also increases. Among household characteristics, a positive and significant coefficient of household dependant members suggests that higher household size is associated with increased emissions.

Based on geographic location, the study reveals intriguing patterns in the use of dung cakes. Compared to other regions, living in a rural area is significantly associated with a higher chance of being included in the sample and using dung cakes. The positive coefficient suggests that, on average, households in rural areas report higher dung cake emissions than their urban counterparts. Furthermore, our analysis of different provinces, KPK, Punjab, and Sindh, reveals variations in reported emissions. With coefficients of KPK for Punjab and Sindh, these figures indicate average emission levels compared to a Balochistan category. These province-based disparities underscore the role of regional factors such as cooking practices, fuel availability, and socio-economic conditions in influencing dung cake emissions. While these findings provide valuable insights into geographical influences, standard errors prompt careful consideration, emphasizing the need for comprehensive research to grasp the intricacies of location-specific emission dynamics better.

4.2.3 LPG Consumption and Emissions

4.2.3.1.1 Determinants of households LPG consumption:

The coefficients of explanatory variables for the first selection stage of the Heckman model are presented in the second column of Table 4.10. Several variables show statistical significance in their relationship with the likelihood of households accessing LPG.

The significant variables like gender and education with a positive coefficient indicate the importance of gender and education in determining the probability of households having access to LPG. This suggests that households led by women are more likely to be included in the sample, implying a higher likelihood of LPG access for these households. This finding throws light on the role of gender in determining access to LPG. According to research, women prioritize using high-quality energy when participating in most household expenditure decisions. This decision is motivated by a desire to save time, improve health outcomes, and have more free time (Rahut et al., 2017). The positive correlations for all education levels imply that households with various educational backgrounds are more likely to have access to LPG. Education has the potential to influence family perceptions, leading to a preference for contemporary fuels. It can also improve decision-makers' comprehension of the benefits and drawbacks of using current kinds of energy.

The computed coefficient for the rural region variable indicates a statistically significant difference in the likelihood of LPG access between rural and urban households. This negative coefficient indicates that rural families are less likely to have access to LPG than their urban counterparts. KPK, Punjab, and Sindh have negative coefficients, indicating a statistically significant drop in the chance of households accessing LPG in their respective regions compared to the reference region. These findings imply that households in KPK, Punjab, and Sindh have less access to LPG, possibly due to regional differences in infrastructure, availability, or socioeconomic factors.

With a negative coefficient of -0.95, the variable clean energy dummy implies that households using alternative clean energy sources other than LPG are less likely to have access to LPG. This research shows a substitution effect between LPG and other clean energy sources, i.e., natural gas and solar energy, where households relying on alternate sources may have lower desire or need for LPG access. Such findings can provide insights into consumer preferences and the dynamics of energy choices in households seeking natural gas or solar energy.

Table 4.10. Results of Household LPG Consumption and Emissions Using Heckman Selection Model and Tobit regression

Factors	LPG Accessibility (Heckman first stage)	LPG Consumption Expenditure (Heckman second stage)	LPG emission (Tobit regression)
Household head characteristics			
Age	-0.0025** (0.000)	-0.005*** (0.000)	0.021 (0.12)
Educated female	0.299*** (0.05)	0.449*** (0.057)	0.994*** (0.180)
Employed head	0.206*** (0.035)	0.086* (0.042)	-0.143 (0.107)
Dependent	-0.02 *** (0.005)	-0.152*** (0.006)	-0.066*** (0.019)
Electricity	0.155*** (0.037)	0.115** (0.04)	-
Household and house characteristics			
Firewood price	0.319*** (0.089)	0.341** (0.106)	2.201** (0.332)
LPG Price	-1.83*** (0.26)	-1.80*** (0.311)	-7.242*** (0.972)
Gas Price	3.67*** (0.30)	2.25*** (0.43)	0.154* (0.092)
Household Expenditure	0.164*** (0.02)	0.07* (0.028)	0.190* (0.077)
AC/Air conditnor	-0.23*** (0.03)	0.20*** (0.03)	-0.542*** (0.120)
No of Rooms	0.09*** (0.00)	0.02* (0.01)	0.315*** (0.031)
Household geographic characteristics			
Rural			
KPK	0.46*** (0.04)	-0.52*** (0.06)	1.293*** (0.183)
Punjab	0.17*** (0.04)	-0.19*** (0.05)	0.389* (0.169)
Sindh	-1.29*** (0.05)	-0.60*** (0.14)	-4.939*** (0.217)
Exclusion restriction variables			
Cooking range ownership		0.22*** (0.03)	-1.661*** (0.354)
Stove ownership			3.228*** (0.103)

Constant	-30.8*** (1.82)	-14.8*** (2.9)	-38.418 *** (4.893)
Model Statistics			
Observations	24,809		
Rho	0.079		
Sigma	0.767		
Pseudo Rsq			0.068

Coefficients are reported with standard errors In parentheses. *= p <0.1, ** = p <0.05, *** = p <0.0
Source: Estimated using 2018-19 HIES data

The coefficients for the second stage of the Heckman model are presented in the 2nd column of Table 4.10. According to the variable's coefficient, households with female heads relate to greater predicted LPG use. According to the positive coefficient, having a female as the head of the family likely plays a substantial role in explaining higher LPG usage. Similarly, if the head is educated, it increases the likelihood of using LPG as cooking fuel and exhibits statistical significance in the expenditure LPG model. Positive coefficients for both variables indicate a relationship between predicted LPG usage and education levels. The correlation between education and LPG consumption is likely due to variables like better financial resources, more awareness of the advantages of clean energy, or a stronger propensity to live in urban regions where LPG is more readily available. Overall, these findings highlight the significance of education as a factor in supporting LPG consumption. Education's importance in helping the transition to contemporary, cleaner cooking fuels has been thoroughly investigated and recorded. Makonese et al. (2018), Nlom and Karimov (2015), and Pope et al. (2018) have all underlined the importance of education in determining the type of primary cooking fuel utilized in households. Formal employment also indicates a higher socio-economic status, often leading to better access to modern and clean fuels such as LPG and natural gas. So educated and formally employed female heads are more likely to recognise the benefits of using cleaner and more efficient cooking fuels like LPG. This increases the likelihood of its adoption in households where females are educated and employed.

With the increase in household-dependant members, the probability of LPG as cooking fuel decreases, and the LPG and fuel consumption per capita consumption of LPG decreases as the household members increase. This may be due to several reasons: households with more dependents may need more financial resources, making it challenging to afford the initial cost of getting LPG cylinders, or they may reside in areas where LPG filling stations are not readily available. The number of rooms in a house also signifies socio-economic status; hence, as the number of rooms increases, the accessibility and per capita consumption of LPG also increases. Hence theousehl nedd more efficient and clean cooking methods.

The availability of electricity and solar panels Signifies access to modern fuel sources and better socioeconomic status. Households with access to electricity or those equipped with solar panels for renewable energy may also be more inclined to adopt LPG for cooking purposes. These households will likely prioritize clean energy options and may have the infrastructure necessary for LPG usage, such as gas pipelines, appropriate storage facilities, and nearby LPG filling stations. Similarly, certain appliances like AC and air coolers negatively impact the likelihood of LPG. This could be due to households prioritising or being powered by other sources like electricity or pipeline gas, so having less demand for LPG.

However, the per capita consumption of those households increases as the status of ownership of these appliances. Similarly, as household expenditure increases, the likelihood and per capita consumption of LPG as cooking fuel increases. It signifies that as asset ownership increases and household expenditure increases, household income rises, and the predicted LPG usage rises, maybe due to increased purchasing power and the capacity to choose LPG as a preferred energy source. The higher firewood prices hurt LPG accessibility and consumption expenditure.

This suggests that as firewood prices increase, households rely more on LPG as an alternative energy source, leading to higher consumption expenditure but improved accessibility. The negative coefficients associated with Sindh province indicate that the likelihood of LPG as cooking fuel and their per capita expenditure on LPG decreases. It indicates that families in these regions use less LPG in the future than those in the other provinces like KPK and Punjab. This suggests that households in Sindh are less likely to use LPG as an energy source, which could be due to regional variances in energy preferences, availability, or cultural traits.

4.2.3.1 Determinants of households LPG emissions:

A dataset of 24,807 observations is used for the Tobit regression, of which 3,865 are uncensored and 20,942 are left-censored (with a lower limit of 0). The statistical study, which includes the chi-square test and the Tobit regression model, provides valuable information on the relationship between several variables and LPG emissions, as shown in Table 4.10. The model effectively captures the data patterns, as evidenced by the high level of statistical significance. Gender, education level, and rural location strongly link LPG emissions. These findings imply that having a female head of the home, having a higher education level, and residing in rural areas are associated with more significant LPG emissions.

The positive coefficient of KPK and Punjab indicates that the LPG emissions in these provinces are way higher than in Balochistan. This suggests that when compared to the reference region, i.e., Balochistan, households in these regions more specifically use more LPG. Similarly, the negative coefficient of LPG emissions for Sindh province suggests that the emissions from LPG are lower in Sindh relative to the reference region. This could be due to various factors such as different cooking practices, access to alternative fuels, or economic conditions. However, it does not directly indicate the level of LPG consumption in Sindh but rather the associated emissions.

These discoveries clarify the variables affecting LPG emissions and aid in our comprehension of the intricate mechanisms at work. LPG emissions are significantly influenced by gender, education level, and geographic location. Female-headed households, greater levels of education, and rural areas are all linked to higher LPG emissions. On the other hand, several areas like KPK, Punjab, and Sindh have lower LPG emissions. Such information can guide policy and intervention plans that encourage using sustainable energy sources and address LPG access and usage discrepancies across various demographic and geographic contexts.

4.2.4 Electricity Consumption and Emissions

4.2.4.1 Determinants of household's electricity Consumption:

The study used a Tobit regression to examine the determinants impacting household consumption expenditures in Pakistan's central provinces. The results of the model are presented in Table 4.11. The coefficient suggests that as the age of household heads increases, per capita expenditure on electricity decreases slightly, although this effect is not statically significant at the conventional level. According to the study findings, housedold with a female head often consume more electricity than those with a male head. This might suggest that homes led by women tend to have higher electricity consumption habits or specific equipment that affect the outcome variable.

There may be a few causes for this relationship. First, compared to homes headed by men, households headed by women could differ in composition. For instance, they might have more dependents or family members, using more energy for heating, cooking, lighting, and other domestic tasks. Additionally, households headed by women may be more likely to have children, resulting in higher energy usage. Likewise, headed households have more significant per capita electricity expenditure.The positive coefficient indicates that educated household heads spend more on electricity per capita. Education can give individuals more job options, excellent salaries, and higher living standards, all of which contribute to the ability to access and pay for energy. Secondly, females are more likely to use electrical appliances or engage in cooking, laundry, and ironing that require high electricity.

Higher degrees of education, as indicated by the variables primary, secondary, and higher education, increase the likelihood of having electricity. Research studies by Bedir et al. (2013) and Ye et al. (2018) show that various factors primarily impact residential energy use. These consist of housing space, household size, urban or rural location, and a few more features unique to the home. These factors contribute significantly to the explanation of the notable differences in household energy use that have been found. Similarly, formally employed households tend to have higher per capita electricity expenditure.

This could be due to the higher income level associated with formal employment, enabling households to afford more electricity and greater use of electrical appliances such as laptop computers. Being an employer increases the expenditure, presumably due to larger salaries and more stable employment. As the coefficient of the number of dependants in a household is negative and significant, it indicates that children and elderly individuals often share common living areas within the house, such as living areas, dining and bedrooms. Multiple family members collectively use these spaces, and there may be fewer separate rooms or areas requiring individual lighting or electronic devices, leading to reduced electricity usage. This is in line with the study of Brounen et al. (2012).

The negative coefficient for rural indicates that households in rural areas tend to have lower per capita electricity expenditures compared to urban areas. This could be attributed to factors such as limited access to electricity infrastructure, less use of electrical appliances and reliance on natural light due to the house structures. Factors like low income and differences in lifestyle preferences in rural settings may also significantly shape electricity consumption patterns. A positive coefficient associated with house ownership suggests that household-owning households tend to spend more on electricity per capita. This could be because house owners are more likely to invest in electrical appliances or amenities that increase electricity usage. Ownership of solar panels and electrical appliances significantly impacts per capita electricity expenditure. Owning a solar panel decreases expenditure, as it decreases the load on grid electricity, while owning an electrical appliance increases it—more electricity.

The coefficients for the regional variables (KPK, Punjab, and Sindh) illustrate regional differences in the likelihood of electricity expenditure. Compared to the reference location, living in Punjab dramatically increases the probability. Investigating the cost and availability of energy in Pakistani provinces shows clear trends and variances. While there is comparably less energy available in Khyber Pakhtunkhwa (KPK), consumption expenditures are significantly greater, indicating that the remaining electricity may be used more intensively or efficiently. On the other hand, Punjab has the most significant availability of electricity in all the provinces, consistent with its far more significant consumption expense and possibly higher usage intensity.

While Sindh's KPK, similarly exhibits a more significant consumption expenditure, suggesting effective utilization. This could be due to factors like higher urbanisation and income levels in Punjab, leading to increased usage for various purposes like residential consumption. Diverse variables, including localized socio-cultural norms, economic situations, infrastructure development, and regional policies, may impact these provincial disparities in electrical dynamics. The results highlight the need for interventions tailored to the unique location. These disparities could be attributed to varying degrees of infrastructural development, government activities, or economic conditions in each location.

Table 4.11. Results of Household Electricity Consumption and Emissions Tobit Model

Factors	Electricity Consumption	Electricity Emissions
Household head characteristics		
Head Age	-0.002* (0.001)	-0.002* (0.001)
Educated female	0.401*** (0.064)	0.404*** (0.065)
Paid employee	0.196*** (0.042)	0.196*** (0.043)
Number of Dependent members	-0.172*** (0.006)	-0.172** (0.006)
Household and house characteristics		
Owned House	0.109** (0.033)	0.112** (0.034)

Factors	Electricity Consumption	Electricity Emissions
No of Rooms	-0.003 (0.011)	-0.005 (0.011)
Solar panel	-1.239*** (0.033)	-1.3*** (0.034)
Electrical appliances	1.004 (0.029)	1.023*** (0.029)
Household Expenditure	0.644*** (0.024)	0.454*** (0.024)
Household geographic characteristics		
Rural	-0.542*** (0.029)	-0.547*** (0.029)
KPK	0.510*** (0.048)	0.516*** (0.049)
Punjab	1.366*** (0.043)	1.384*** (0.044)
Sindh	0.549*** (0.046)	0.556*** (0.047)
Constant	-4.786*** (0.311)	-4.834*** (0.317)
Model Statistics		
Observations	22,000	
Pseudo Rsq		0.56

Coefficients are reported with standard errors in parentheses. *= p <0.1, ** = p <0.05, *** = p <0.0
Source: Estimated using 2018-19 HIES data.

The second stage of the various variables is older people, family members, and particularly adults more considerable The coefficient of total expenditure suggests that as the total expenditure increases, the per capita consumption expenditure also increases. This observation aligns with intuition, as higher overall expenditure indicates greater household financial capacity. With increased financial resources, households are likely to afford more electrical appliances, gadgets or services or services that require electricity, thereby contributing to higher electricity expenditure per capita.

4.2.4.1 Determinants of Household's Electricity Emissions

Determinants of household's electricity emissions are presented in Table 4.11. Household head age has a substantial low impact on electricity emissions. the negative coefficient indicates that a marginal negative association between head age and per capita electricity emissions. this implies that as head age increases, a slight decrease in energy usage might lead to a slight decrease in electricity emissions. One possible reason could be that older individuals share space with other family members and the need to use electricity appliances decreases .

The coefficient of head's gender indicates that households with a female head have roughly more electricity emissions than households with a male head. The significant association shows that having a female household head is related to more significant electricity emissions. Several factors can influence the link between having a female head of household and higher electricity emissions. At the outset, women-headed households may have different compositions than male-headed households. They may include more household members or dependents, resulting in greater energy consumption for domestic tasks such as cooking, heating, and childcare.

The presence of additional people in the family correlates to higher electricity consumption. It is vital to emphasize that the "Female Headed Household" variable should be interpreted as it signifies a direct association between gender and electricity emissions. The coefficient indicates a link but does not reveal anything about the underlying mechanisms or the exact contextual elements that influence this relationship. The statistical significance of this factor in the regression analysis suggests that there is statistical evidence of a positive connection between female-headed households and more significant electricity emissions. Still, additional study and analysis are required to comprehend this association better.

According to the findings, as education levels rise, so do electricity emissions. Higher education levels may be associated with higher earnings, better access to energy-consuming devices, and increased awareness of energy-efficient practices. Educated females may adopt more modern lifestyles that involve more significant electricity usage, such as using electronic devices for work and leisure activities. These factors can all contribute to increased energy consumption habits and, as a result, higher electricity emissions.

In the regression analysis, the employment variables provide insight into the relationship between job status and electricity emissions. Households with employed heads have more significant electricity emissions, demonstrating that working for someone else is connected with higher energy usage. This could be because these households have greater income levels, allowing them to acquire energy-intensive electronic devices and technologies. Furthermore, specific jobs or sectors may highly include energy-intensive activities, contributing to increased power use.

It is crucial to note that these links are based on accessible data and statistical analysis and that individual behaviors and contextual factors might influence energy usage trends. More study and analysis are required to investigate the mechanisms and contextual elements influencing the connections between employment status and power emissions.

Sharing appliances is common in households with more dependents, resulting in lower per capita electricity emissions. Individual members do not typically use separate electronic devices, leading to reduced overall electricity usage per person. Additionally, having more dependents prompts households to be more conscious about energy consumption and make efforts to reduce energy wastage. Together, these factors contribute to lower per capita electricity emissions. Households who own their homes tend to have higher electricity emissions per capita. One possible reason for this could be that homeownership is often associated with higher socio-economic status, which may lead to greater access to and use of electricity-consuming amenities and appliances. The coefficient for Solar panels is negative, and for electrical appliances is positive, indicating significant associations with per capita electricity emissions. While owning solar panels may initially appear counterintuitive with its negative coefficient, it suggests that households with solar panels tend to have lower per capita electricity emissions. Solar panels generate electricity using renewable energy sources, reducing reliance on conventional grid electricity and lowering emissions. Conversely, owning electrical appliances leads to higher electricity emissions due to increased electricity usage for operating these appliances.

The rural region attribute specifies whether the residence is in a rural area. The coefficient indicates that households in rural areas have fewer electricity emissions than households in non-rural areas. Because of this negative coefficient, living in a rural area relates to reduced electricity emissions. Rural homes frequently have distinct energy usage habits than urban households. They may rely more on conventional and low-energy-consuming cooking and heating sources, such as biomass or wood, resulting in decreased power consumption. Additionally, lifestyle differences between rural and urban areas can influence electricity usage patterns. Rural areas may have a different mix of economic activities and household chores that require less reliance on electricity. For example, agricultural activities or manual labour in rural areas may require less energy-intensive equipment than industrial or commercial activities in urban areas.

Moreover, housing characteristics in rural areas may differ, with traditional or less energy-intensive building designs being more prevalent. This can reduce electricity usage for heating, cooling, or lighting purposes. Furthermore, access to contemporary energy-consuming equipment and appliances in rural locations may be limited, contributing to fewer emissions.

This coefficient suggests that households in KPK may consume more electricity than other provinces. Climate, socioeconomic conditions, and energy access are all elements that might contribute to these disparities. For example, KPK has a variety of climates, including hot summers and chilly winters, which might result in increased energy usage for cooling and heating. The positive coefficient indicates that households in Punjab have more electricity emissions than households in other provinces. Punjab is Pakistan's most populous province, with higher levels of industry and urbanization. These elements may result in increased energy usage and emissions.

Furthermore, Punjab has a variety of temperatures, ranging from hot and arid in the south to slightly colder in the north, which contributes to a wide range of energy needs and consumption patterns. The coefficient of Sindh emits approximately more electricity than households in the reference category. Sindh is noted for its hot and humid climate, especially along the shore. Higher energy demand for cooling in such areas may increase electricity emissions. Furthermore, Sindh is home to significant metropolitan centres, notably Karachi, which has a high population density and energy consumption, which influences emissions further.

4.2.4.1.1 Econometric Analysis Household Food Consumption and Emissions:

The study utilized multiple regression analyses to anticipate household food consumption and emissions determinants for food groups like grains, dairy, fruits, and veggies.

4.2.4.1.1.1 Household Food Consumption and Emissions

This study delves into the intricate relationship between household grain consumption and emissions, seeking to discern patterns, relationships, and potential implications. By employing multiple regression analysis, as shown in Table 4.12, this research aims to unravel the complex interplay between the quantities and types of grains households consume and the resultant emissions footprint.

Investigating family consumption patterns gives intriguing details on food preferences impacted by various circumstances, as shown in **Table 4.12**. Education emerges as a critical determinant, with families led by educated females consuming considerably more across all dietary categories - grains, dairy, and vegetables/fruits. Conversely, the number of dependents in a home appears to have a balanced impact, with bigger households consuming fewer grains and vegetables/fruits but more dairy. Employment status negatively impacts dairy consumption, meaning families with paid employees consume less. Possibly due to more prominent families or established dietary habits, elderly heads of households tend to devote more money on grain costs.

Possibly due to differences in their dietary preferences, households headed by women spend more money in this area. Furthermore, socioeconomic factors such as household income significantly influence consumption patterns, with higher expenditures related to increased consumption levels in all food categories. Regional differences are also noticeable, with rural households usually consuming more grains and dairy than urban counterparts, but with lower vegetable/fruit intake. Notably, regional variances reflect subtle dietary choices, with Punjab families consuming fewer grains but more dairy than other areas, whereas Sindh households consume more overall. These findings highlight the complex interaction of demographic, socioeconomic, and geographical factors in creating dietary habits and the importance of targeted interventions to encourage better eating behaviors.

Table 4.12: Results of Household food Consumption using Regression Analysis

Factors	**Grains consumption**	**Dairy consumption**	**Vegetables and fruits**
	Coefficients	**Coefficients**	**Coefficients**
Household head characteristics			
Head Age	0.0026*** (0.006)	0.002*** (0.003)	-0.002*** (0.0005)
Female educated	0.20*** (0.005)	0.087*** (0.000)	0.37*** (0.03)
Number of dependant members	-0.046*** (0.004)	0.014*** (0.003)	-0.13*** (0.003)
Paid employee	-0.0352 (0.023)	-0.143*** (0.001)	-0.022 (0.018)
Household expenditure	0.06*** (0.004)	0.08*** (0.00)	0.005*** (0.000)
Rural	0.36*** (0.000)	0.15*** (0.014)	-0.109*** (0.015)
KPK	-0.12*** (0.002)	-0.336*** (0.002)	.0.009*** (0.002)
Punjab	-0.79** (0.03)	0.313*** (0.23)	0.168*** (0.026)
Sindh	0.211** (0.033)	0.28** (0.02)	0.115** (0.02)
Constant	5.83***	5.95***	3.82***

Factors	Grains consumption	Dairy consumption	Vegetables and fruits
	(0.04)	(0.034)	(0.037)
Model Statistics			
Observations	24,809	24,809	24,809
R^2	0.20	0.27	0.15

Coefficients are reported with standard errors in parentheses. *= p <0.1, ** = p <0.05, *** = p <0.0

The analysis of household emissions reveals several significant factors influencing these emissions, as shown in Table 4.13. Education emerges as a critical predictor, with households led by educated females emitting more emissions across all food categories, including grains, dairy, and vegetables/fruits. In contrast, the number of dependents in a home appears to have a moderating impact, with more prominent families reporting lower emissions for grains and vegetables/fruits but somewhat higher emissions for dairy products. Employment status has a significant impact, notably on dairy emissions, indicating that families with paid employees emit less in this category.

Furthermore, socioeconomic factors such as household expenditure significantly influence emission levels, with more significant expenditures resulting in higher emissions across all food categories. Regional differences are also observed, with rural households emitting less for grains and vegetables/fruits but more for dairy than urban counterparts. Notably, regional differences highlight subtle emission patterns, with Punjab households releasing less grains but significantly more in dairy than other areas, whereas Sindh households emit more overall. These findings emphasize the complex interplay of demographic, socioeconomic, and geographical factors in generating dietary emissions, emphasizing the importance of tailored initiatives to reduce environmental consequences while maintaining food security and nutrition.

Our results highlight the complex interactions among socioeconomic, demographic, and regional factors influencing home emissions, offering critical information for focused environmental legislation or public awareness initiatives.

Table 4.13:Results of Household Food Emissions using Regression Analysis

Factors	**Grains Emissions**	**Dairy Emissions**	**Vegetables and fruits emissions**
	Coefficients	**Coefficients**	**Coefficients**
Household head characteristics			
Head Age	-0.009*** (0.006)	0.003*** (0.003)	-0.002*** (0.0005)
Female educated	0.26*** (0.005)	0.07*** (0.000)	0.33*** (0.03)
Number of dependant members	-0.03*** (0.004)	0.012*** (0.003)	-0.07*** (0.003)
Paid employee	-0.08*** (0.013)	-0.13*** (0.001)	-0.013 (0.04)
Household expenditure	0.06*** (0.004)	0.01*** (0.00)	0.012*** (0.000)
Rural	-0.10*** (0.000)	0.22*** (0.014)	-0.322*** (0.015)
KPK	-0.08*** (0.002)	0.06*** (0.002)	.0.22*** (0.002)
Punjab	-0.24** (0.03)	1.06*** (0.23)	0.28*** (0.026)
Sindh	0.59** (0.033)	0.85** (0.02)	0.06** (0.02)
Constant	4.53*** (0.04)	3.68*** (0.034)	2.76*** (0.037)
Model Statistics			
Observations	24,809	24,809	24,809
R^2	0.20	0.24	0.15

Coefficients are reported with standard errors in parentheses. *= p <0.1, ** = p <0.05, *** = p <0.0

4.2.5 Cooking Emissions and Environment Kuznets Curve

The Environmental Kuznets Curve (EKC) hypothesis is a well-known idea in environmental economics that attempts to explain the link between economic development, environmental quality, and pollutant emissions. It posits that when economies expand and per capita income grows, there will be an initial period of increased environmental deterioration and pollutant emissions. This happens because there is typically a significant reliance on resource-intensive sectors and energy sources in the early phases of economic growth, leading to increased pollution levels.

However, the EKC theory argues that environmental circumstances improve after a certain level of affluence or development. As economies improve, they invest in cleaner technology, employ more efficient manufacturing processes, and impose more substantial environmental restrictions. These actions may result in a decline. The EKC idea has been widely researched concerning numerous pollutants, such as CO_2 emissions, SO_2 emissions, and other environmental indicators. We are researching its relevance to cooking emissions and cooking expenses in this specific situation. Cooking emissions are the pollutants released during the cooking process, such as particulate matter (PM), carbon monoxide (CO), and volatile organic compounds (VOCs). These emissions are frequently linked to traditional cooking practices that use solid fuels such as wood, charcoal, and dung cakes in open flames or inefficient stoves. In this study, cooking expenditure is a proxy for income or economic growth. Households tend to spend more on cooking fuels and related expenditures as economies and incomes develop, resulting in increased cooking expenditures.

The EKC hypothesis can be used to explain the link between cooking emissions and cooking expenses. If the EKC pattern holds, we should anticipate cooking emissions to grow first when cooking expenditure rises with economic development, reflecting increased usage of conventional and inefficient cooking fuels. However, emissions may begin to fall after a certain level of cooking expenditure due to the advent of cleaner cooking technology and improved cooking practices. The study estimates the EKC hypothesis of cooking fuel only out of the total consumption expenditures as it is evident from the results of cooking fuel, electricity and food consumption that cooking fuels contribute the major chunk of emissions. Given their significant contribution to residential emissions overall, cooking fuel emissions must be the primary focus of household study. Cooking may be a significant source of emissions, particularly in areas with prevalent traditional or inefficient cooking methods. These emissions, which contribute to indoor and outdoor air pollution and greenhouse gas emissions, are caused mainly by burning solid fuels like wood, dung cake, or biomass.

On the other hand, while they may still have an effect, food and electricity consumption emissions may contribute less to household emissions than cooking fuels. The energy mix of an area may affect how much electricity is used, and other factors, including the techniques used to produce food, can impact emissions linked to eating preferences.

A regression analysis investigates this association, integrating variables related to cooking emissions, cooking expenditures and socio-economic and dwelling parameters. The regression results can reveal the direction and degree of the association between these variables and if the EKC pattern is visible.

Table 4.14 Regression results for Cooking fuel expenditure and emissions

Factors	**Coefficients**
Cooking Expenditure	0.59* (0.02)
Cooking expenditure^2	-0.02*** (0.019)
Dependency Ratio	0.04 (0.05)
Illiterate	0.23 (2.081)
Primary Education	0.01 (0.05)
Secondary Education	-0.08 (0.05)
Paid employee	-0.15* (0.03)
Detached house	0.53** (0.05)
Attached house	0.60*** (0.10)
Semi-detached house	0.62*** (0.06)
RCC roof	0.19 (0.15)
Wooden roof	0.80*** (0.15)
Sheet roof	0.15 (0.14)
Iron roof	0.48** (0.15)
Clean energy	-0.06** (0.03)
Household geographic characteristics	
KP	0.29*** (0.05)
Punjab	0.85*** (0.05)
Sindh	0.38*** (0.05)
Constant	-33.2469*** (3.193)
Model Statistics	
Observations	24,809
R^2	0.41

The results in Table 4.14 indicate that as Households spend more on cooking, there is a corresponding increase in cooking emissions(hmad et al., 2015; Kavi et al., 2013; Kulkarni et al., 2022; Qudrat-Ullah, 2022). This positive relationship suggests that as households allocate more funds towards cooking fuels, fuel consumption rises, leading to more significant emissions. This can be attributed to higher expenditure often means increased usage of available fuels, which, depending on the fuel type, can lead to higher emissions. This aligns with the initial phase of the Environmental Kuznets Curve (EKC) hypothesis, where higher economic growth and spending on cooking fuels might lead to higher emissions. Each additional member in the household is associated with a significant increase of 0.08 units in cooking emissions.

Larger households tend to cook more food, resulting in higher emissions. With more members to feed, households may require more cooking activities, leading to increased use of cooking fuels and emissions. Education plays a crucial role in influencing cooking emissions, but the impact varies depending on the level of education. Illiteracy is associated with higher emissions, likely due to a lack of awareness, low income level and understanding of efficient and cleaner cooking practices. However, primary and secondary education alone do not significantly reduce emissions, possibly due to economic constraints and the persistence of traditional practices.The analysis results align with Barnes et al., 1994; Rehfuess et al., 2014; Ruiz-Mercado et al., 2011.

This highlights the need for comprehensive educational programs that increase general literacy and provide specific knowledge about the benefits and use of clean energy technologies. Addressing economic barriers to accessing cleaner fuels is essential to complement educational efforts. Cooking emissions are higher in KP, Punjab, and Sindh compared to the reference category (Balochistan). This suggests regional variations in cooking practices and fuel usage. Higher cooking emissions in regions like Khyber Pakhtunkhwa (KP), Punjab, and Sindh compared to Balochistan can be attributed to a combination of factors. The higher population density and increased urbanization increase demand for cooking activities, resulting in elevated emissions from cooking fuels.

Variations in cooking practices, such as using traditional methods and inefficient stoves, along with disparities in access to clean cooking technologies, contribute to higher emissions in these regions. Additionally, climate conditions, economic factors, and cultural preferences shape cooking patterns and fuel choices, potentially leading to higher emissions in areas with extreme weather conditions, lower economic development, and specific culinary traditions. Addressing these factors through targeted interventions and policies can help promote cleaner cooking practices, improve access to clean cooking technologies, and mitigate cooking emissions in regions like KPK, Punjab, and Sindh. paid employees have lower cooking emissions than those who are self-employed. Studies such as Bailis et al. (2001), Rehman et al. (2020) , and Zhang et al. (2011) have examined the relationship between employment status and cooking emissions in households.

They have found that households with paid employees tend to have lower cooking emissions than self-employed households. This difference is attributed to factors such as income stability, access to benefits, better education and awareness, convenience, and the ability to prioritize investments in clean energy among households with paid employees. The structure and support associated with paid employment facilitate adopting cleaner and more efficient cooking practices, reducing emissions. Addressing the specific challenges self-employed individuals face, such as income volatility and limited access to resources, can play a crucial role in further reducing cooking emissions across different employment types.Households with more rooms tend to have lower cooking emissions.

This could be due to larger houses having more efficient kitchen setups or access to cleaner cooking technologies. This relationship implies that household characteristics, such as house size and kitchen facilities, can influence cooking emissions. By having more rooms, households may have better ventilation, more space for energy-efficient appliances, or access to cleaner cooking fuels, all of which can contribute to lower cooking emissions. This highlights the importance of considering household characteristics and technologies in understanding and potentially reducing emissions from cooking activities. Studies such as Smith et al. (2000), Bailis et al. (2001), and Rehman et al. (2020) have explored the relationship between household characteristics, cooking emissions, and indoor air quality. These studies have highlighted the significance of house size, kitchen setups, and cooking technologies in influencing emissions from cooking activities.

The findings suggest that households with more rooms or access to cleaner cooking technologies may exhibit lower cooking emissions due to improved ventilation, energy-efficient appliances, or cleaner fuel sources. Detached houses are associated with higher emissions, likely due to their larger size, reliance on traditional biomass fuels like firewood and dung cakes, and space for less efficient cooking methods such as open fires or wood stoves.

Similarly, semi-detached houses significantly positively impact emissions. Attached houses also contribute to higher emissions despite typically being in urban settings where cleaner fuels might be more accessible. This could be due to the cumulative effect of many households using substantial volumes of fuel, as well as potential issues with ventilation, leading to the accumulation of emissions indoors. The type of roofing material further influences emissions. Houses with wooden roofs have significantly higher emissions, possibly due to older construction methods and poorer insulation requiring more fuel for cooking and heating.

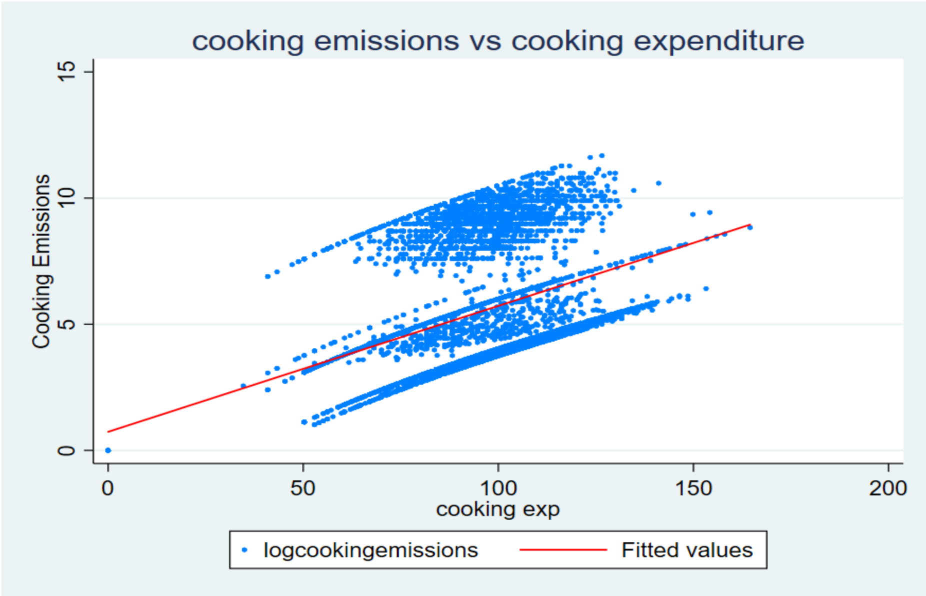
Similarly, iron roofs are associated with higher emissions, potentially due to poor heat retention and the economic indicator of lower-income households relying on cheaper, more polluting fuels. In contrast, houses with RCC (reinforced concrete) roofs do not significantly impact emissions, suggesting that modern construction materials may not strongly correlate with specific fuel use patterns affecting emissions. Studies such as Reddy and Patel (2011), and Zhang et al. (2011) have investigated the impact of roofing materials on emissions and household fuel use patterns.

These studies have found that houses with wooden roofs tend to have significantly higher emissions, possibly due to older construction methods and poorer insulation, leading to increased fuel consumption for cooking and heating. Similarly, iron roofs have been associated with higher emissions, potentially attributed to poor heat retention and the economic indicator of lower-income households relying on cheaper but more polluting fuels. In contrast, houses with reinforced concrete (RCC) roofs do not significantly impact emissions, suggesting that modern construction materials may not strongly correlate with specific fuel use patterns that affect emissions.

The graph showing a continuous and upward linear trend in cooking emissions as cooking expenditure increases indicates evidence of the Environmental Kuznets Curve (EKC) pattern in the relationship between these variables.

Without the EKC pattern, the graph suggests that cooking emissions do not follow the expected inverted U shape as household expenditure increases, where emissions initially rise and decline after reaching a certain income or expenditure level. Instead, the graph indicates a direct and proportional relationship between cooking emissions and cooking expenditure, as shown

Figure 4.1: Relationship between cooking emissions and expenditure



The absence of the Environmental Kuznets Curve (EKC) pattern in the relationship between cooking emissions and cooking expenditure holds significant implications. The linear upward trend observed in the graph signifies that as cooking expenditure increases with economic growth, there is a corresponding rise in cooking emissions. This finding suggests that economic development has not yet translated into adopting cleaner cooking technologies or practices, typically leading to reduced emissions. This raises environmental concerns, as unabated emissions can contribute to air pollution, adversely affecting public health and contributing to climate change. Therefore, there is a pressing need for sustainable solutions in the cooking sector. Initiatives promoting cleaner energy sources and more efficient cooking technologies are vital for mitigating cooking emissions and reducing their environmental impact.

One probable cause might be the disproportionate increase in the cost of cleaner fuels relative to their more polluting competitors and stagnating household incomes. This situation may encourage average-income households to use cheaper yet more ecologically hazardous fuels. As shifting to cleaner alternatives rises, households may continue with the less expensive but polluting solutions despite possible environmental consequences. Policymakers and researchers should carefully examine the factors underlying the absence of the EKC pattern and consider reevaluating existing policies and developing targeted interventions to encourage adopting cleaner cooking practices, particularly in regions where cooking emissions remain a significant environmental challenge. Socioeconomic factors like cultural and behavioral influences will likely shape the relationship between cooking emissions and expenditures. These complexities can offer valuable insights into the design effects of designing cues and programs that foster environmentally friendly cooking practices while achieving balancing progress and environmental preservation.

4.2.6 Spatial patterns of Household Emissions

This study explores the spatial patterns of household-level emissions in Pakistan's provinces, namely Khyber Pakhtunkhwa (KPK), Punjab, Sindh, and Balochistan. I analyzed household fuel consumption and emissions in my study and utilized ArcGIS mapping to visualize the findings. Initially, provincial-level data was analyzed, which was then disaggregated into divisions. Following this, I mapped the household data according to these divisions to better understand and visualize the patterns and distribution of emissions. The process involved converting the provincial-level data into divisions to provide a more granular and localized perspective. Spatial differentiation research encompasses a variety of methods, with Exploratory Spatial Data Analysis (ESDA) being a commonly utilized approach. ESDA encompasses a range of techniques and technologies for analyzing spatial data, focusing on global and local spatial patterns.

At its core, ESDA involves measuring spatial correlation to identify potential spatial relationships within data and uncover spatial anomalies and clustering phenomena. Furthermore, ESDA emphasizes the concepts of Spatial Dependence and Spatial Heterogeneity, which are crucial for accurately describing the spatial distribution characteristics of research subjects. By acknowledging these concepts, ESDA lays the groundwork for uncovering the underlying mechanisms driving spatial patterns. Legendre (1993), Arthur (2001), and Hu et al. (2015) have contributed significantly to the development and application of ESDA techniques, providing valuable insights into the field of spatial analysis and its relevance in various research domains.

Initially, this study investigated spatial coherence across the entire study area using the ESDA method of Moran’s I, as Rong et al.(2018) outlined. Subsequently, the study further examined the spatial variation of local spatial units within the study area using the local indicators of spatial association(LISA) method to address the constraint of analyzing data at a global scale.

The results of the global spatial autocorrelation analysis are presented in Table 4.15. For most types of carbon emissions (except carbon emissions from coal), the Z value of the average statistic exceeded 1.96 at a confidence level of 0.05. The corresponding P values were less than 0.05, indicating that these household carbon emissions passed the significance test. This suggests household carbon emissions exhibit non-random distribution and display specific spatial positive correlation characteristics.

However, it is essential to note that the global spatial autocorrelation analysis hypothesis assumes spatial smoothness, which may only sometimes hold in practice, especially when dealing with large amounts of data. In such cases, the assumption of spatial stationarity becomes unrealistic. Therefore, we introduced the local method better to understand the spatial characteristics of various household carbon emissions.

The Local Indicators of Spatial Association (LISA) measures the degree of similarity, divergence, and significance between the attributes of spatial units and their neighbouring units.

Table 4.15: Estimation of Moran's I for household energy consumption

Carbon Emission type	**Moran's I**	**P value**
Household carbon emission from firewood	0.076	0.05
Household carbon emission from Dungcake	0.0219	0
Household carbon emissions from LPG	0.0254	0.01
Household carbon emissions from Natural gas	0.019	0.01
Household carbon emission from Electricity	0.25	0.01

The Moran's I value for household carbon emissions from firewood, dung cake, and electricity indicate some spatial autocorrelation. However, only the electricity emissions show a high level of spatial clustering (Moran's I = 0.25). However, it is essential to note that the significance level varies across different types of emissions. At a significance level of 0.05, only the household carbon emissions from firewood and dung cake exhibit statistical significance. This suggests that for these two emission types, the spatial autocorrelation is significant at the 0.05 confidence level, meaning that similar values are clustered together in space for these emissions.

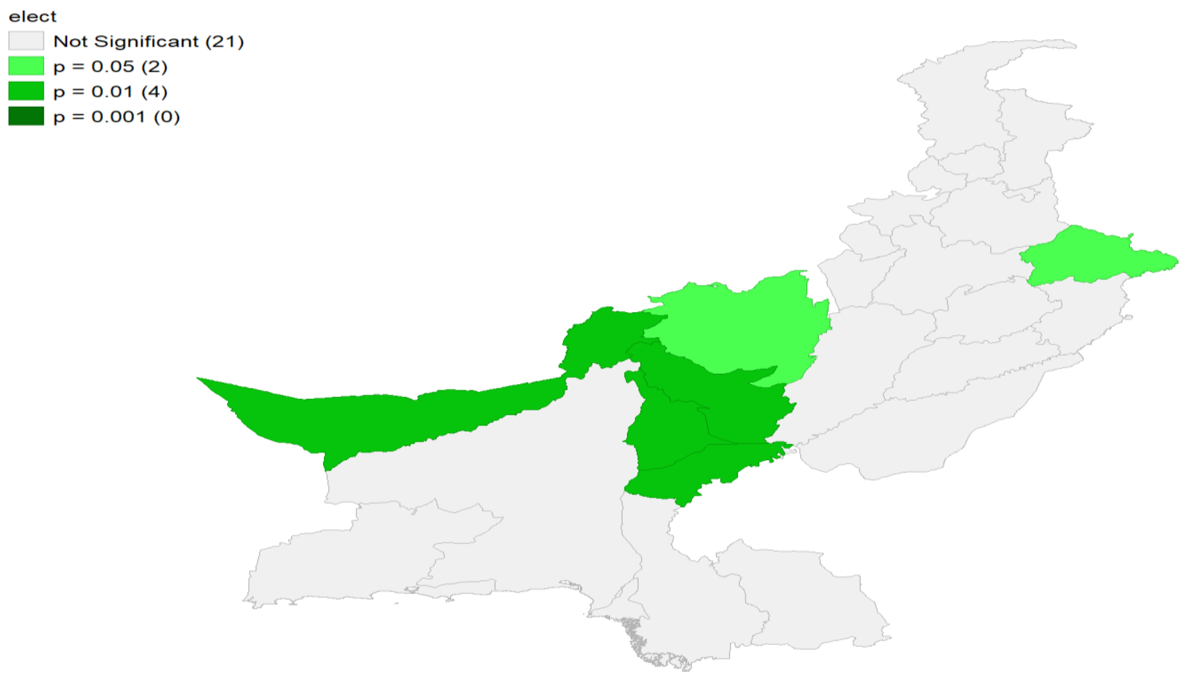
For household carbon emissions from LPG and natural gas, the spatial autocorrelation is significant at a stricter level of significance (P value < 0.01). This indicates a higher confidence level in the spatial clustering of these emissions compared to firewood and dung cake. Overall, while there may not be significant spatial autocorrelation for all types of household carbon emissions, statistical significance for firewood, dung cake, LPG, and natural gas emissions underscores the importance of considering spatial patterns when analyzing carbon emissions at the household level. Further investigation using local spatial methods could provide deeper insights into these emissions' spatial distribution and clustering within the study area.

4.2.6.1 Household Electricity Carbon Emissions:

The LISA cluster map for electricity emissions, as shown in Figure 4.2, indicates two clusters. One is the high cluster, identified as the Gujranwala division—and the low, low cluster is Quetta and Sibbi.

Identifying a High cluster in Gujranwala suggests a concentrated area with high household carbon emissions from electricity. Surrounding regions also exhibit similarly high emissions, indicating a localized pattern of heavy reliance on electricity for household energy needs. Possible reasons include urbanization, industrialization, or infrastructure development in the Gujranwala region and increasing household electricity consumption. A Low-Low cluster in Quetta and Sibbi signifies regions with consistently low household carbon emissions from electricity. This indicates a pattern of reduced reliance on electricity for energy needs among households in these areas. Possible factors contributing to this lower electricity consumption include limited access to electricity infrastructure, economic constraints, or alternative energy sources such as solar or wind power.

Figure 4.2: LISA cluster Map of Household Electricity Emissions



Variations in emissions can be ascribed to variables such as population density, industrial activity, energy consumption habits, and the availability of cleaner energy sources in each province. Understanding these distinctions is critical for developing targeted environmental regulations and promoting sustainable energy practices globally.

4.2.6.2 Household Firewood Emissions

Figure 4.3 depicts household-level statistics on emissions from the use of firewood for cooking and heating in several Pakistani regions. Firewood is a typical traditional fuel used in houses, particularly in rural regions. However, it can cause the emission of pollutants such as particulate matter and carbon monoxide, affecting indoor air quality and contributing to pollution. Understanding how firewood emissions differ among provinces is critical for developing targeted interventions to promote cleaner cooking technology and sustainable energy practices. The LISA cluster map shows three main clustering patterns.

1. **High-High Cluster (Bannu, KP):**

The presence of a High cluster in Bannu, Khyber Pakhtunkhwa (KP), suggests that this area exhibits high household carbon emissions from firewood and is surrounded by neighbouring areas with similarly high emissions. This clustering indicates a localized concentration of households relying heavily on firewood for energy needs. Possible reasons for this include limited access to alternative fuels, socio-economic factors, or cultural preferences favouring traditional cooking methods. The more significant firewood emissions in KPK can be linked to the province's large rural population, which uses traditional cooking methods. Rural households' reliance on firewood for cooking and warmth contributes to the emissions recorded in this province.

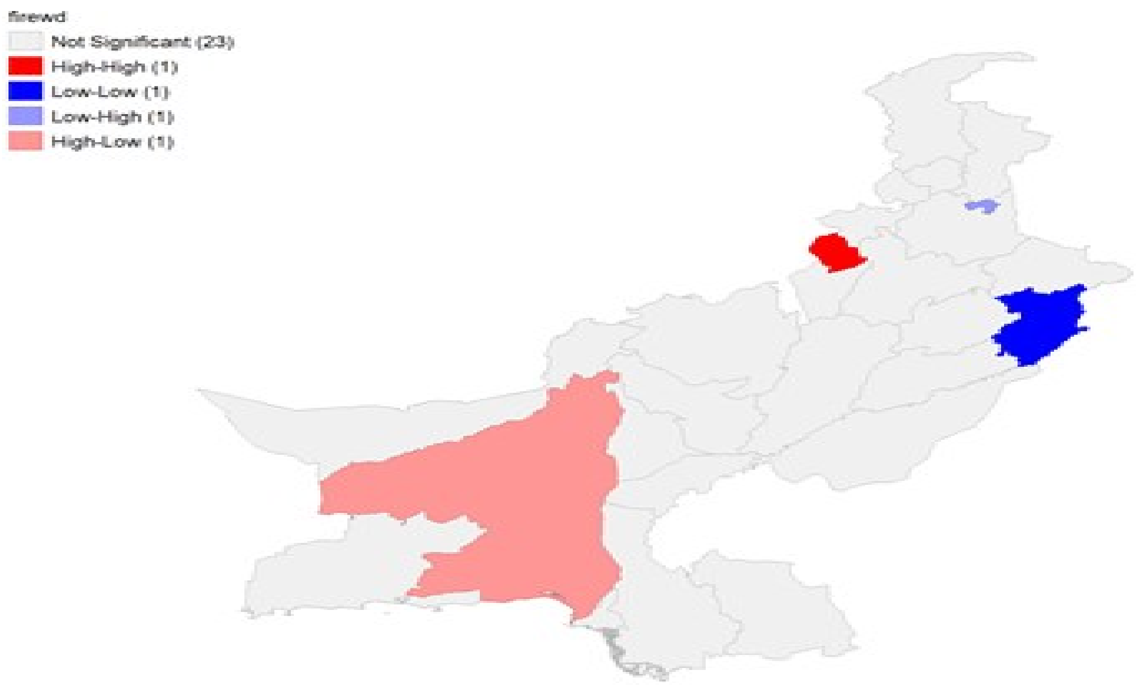
2. **Low-Low Cluster (Lahore):**

Conversely, a Low-Low cluster in Lahore indicates that this area exhibits relatively low household carbon emissions from firewood, surrounded by neighbouring areas with similarly low emissions. This suggests a distinct pattern of reduced reliance on firewood among households in Lahore compared to surrounding regions. Possible factors contributing to this lower reliance on firewood include greater access to cleaner fuels, such as LPG or electricity, or differences in socioeconomic status.

3. **High-Low Outlier (Kalat):**

A High-Low outlier in Kalat suggests a unique spatial pattern where this area has relatively high levels of household carbon emissions from firewood compared to its neighbours despite being surrounded by areas with lower emissions. This outlier pattern could be attributed to localized factors such as environmental conditions, economic activities, or cultural practices that influence fuel use patterns in Kalat.

Figure 4.3: LISA Map of Household Firewood Emissions

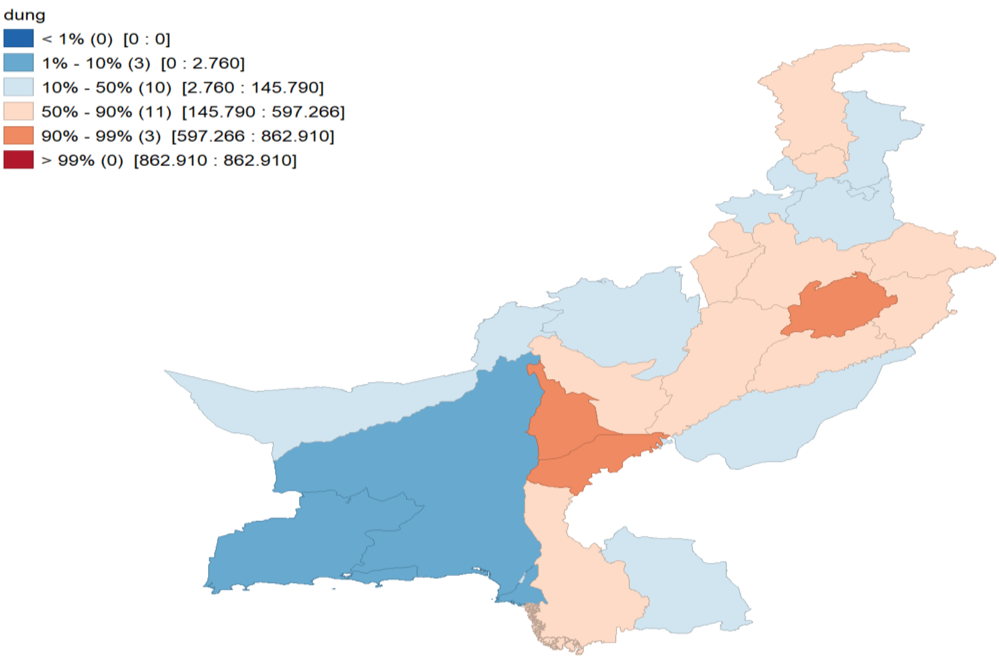


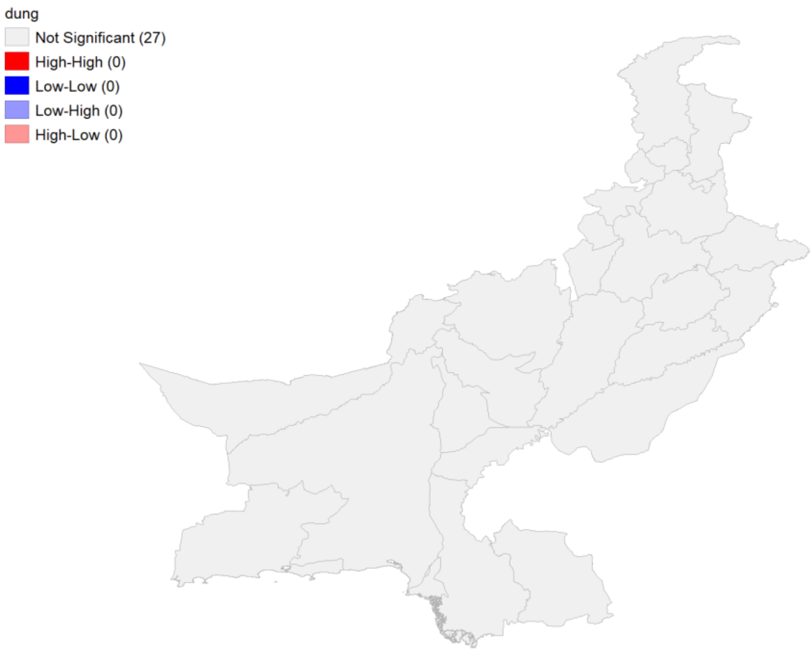
The data highlights the need for focused efforts to mitigate the environmental effect of conventional cooking methods by revealing regional differences in firewood emissions. For cutting down on firewood emissions, enhancing interior air quality, and lowering environmental pollution, it is crucial to encourage the adoption of clean and energy-efficient cooking methods. In line with Pakistan's larger sustainability objectives, policymakers may use this data to create region-specific programs that promote the adoption of cleaner cooking technology and improve sustainable energy practices. The nation can significantly advance its efforts to combat climate change, improve public health, and ensure a more ecologically conscious future by tackling firewood emissions.

4.2.6.3 Households Dung Cake Emissions

Dung cakes are frequently used for cooking and heating in many rural Pakistani communities, particularly in homes with little access to contemporary energy sources. Burning dung cakes emit carbon monoxide, particulate matter, and other toxic gases into the air, contributing to air pollution and detrimental impacts on human health. shows dung cake emissions in Pakistan by division, measured in metric tonnes. The percentile map of household dung cake emissions indicates that more than 50 per cent of the population is using dung cake as a cooking source widespread among Punjab and KPK, but the LISA cluster map indicates that there is no significant clustering of low or high is prevalent in all divisions of Pakistan as shown in **Figure 4.4**.

Figure 4.4: Percentile Distribution and LISA Map of Households Dung Cake Emissions





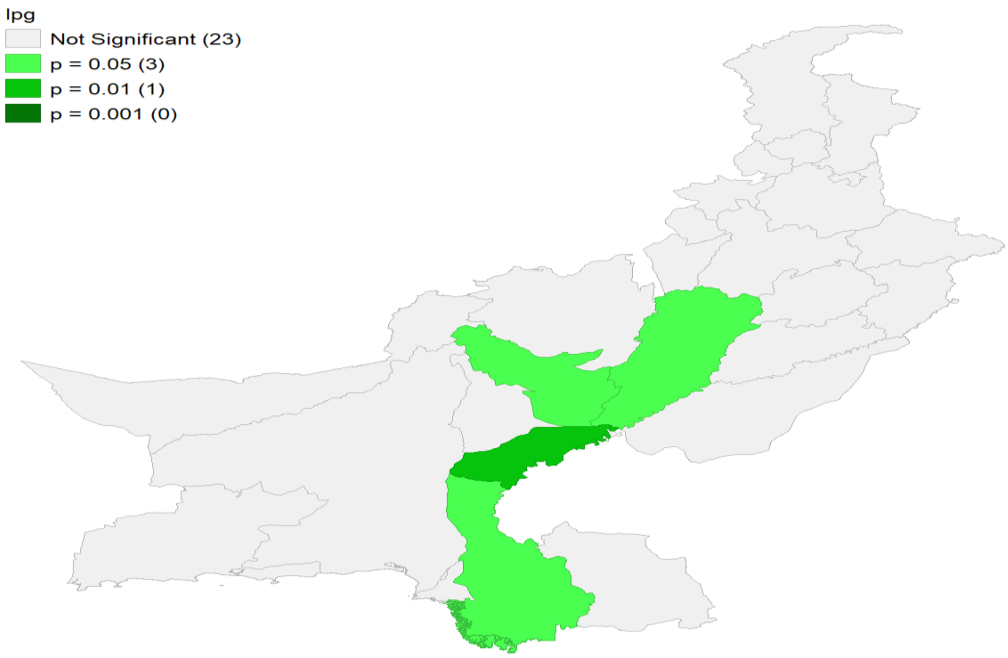
Dung cake emissions are the pollutants and greenhouse gases released during the combustion of dung cakes as traditional cooking fuel. The higher emissions in Khyber Pakhtunkhwa (KPK) are due to the extensive usage of dung cakes in rural regions, which serve as a cheap and readily available fuel source. Punjab has the most significant dung cake emissions. With its vast population and mix of rural and urban environments, Punjab has a high demand for cooking fuels, contributing to the state's high emissions—Sindh metric tonnes of dung cake emissions, which are impacted by both rural and urban practices. The findings show that dung cake emissions are a major environmental problem, particularly in areas with large rural populations. Because dung cakes are a significant source of interior air pollution and contribute to outdoor air pollution, initiatives to promote cleaner and more sustainable cooking practices are required. Encouraging clean cooking technology and the availability of better energy sources can help reduce dung cake emissions, enhance air quality, and protect public health in these areas.

Pakistan may develop towards a more sustainable and environmentally friendly energy landscape by introducing targeted policies and activities that address the issues associated with conventional cooking fuels. Reduced dung cake emissions would help the environment and the well-being and livelihoods of people who rely on them.

4.2.6.4 Households LPG emissions

Liquefied petroleum gas (LPG) is a cleaner and more efficient cooking fuel than conventional solid fuels such as firewood and dung cakes. It is well-known for its minimal emissions and low environmental effects. Understanding the distribution of LPG emissions across provinces can give important insights into adopting cleaner cooking practices and the possible environmental advantages of LPG use, as shown in Figure 0.5.

Figure 0.5: LISA Map of Households LPG emissions

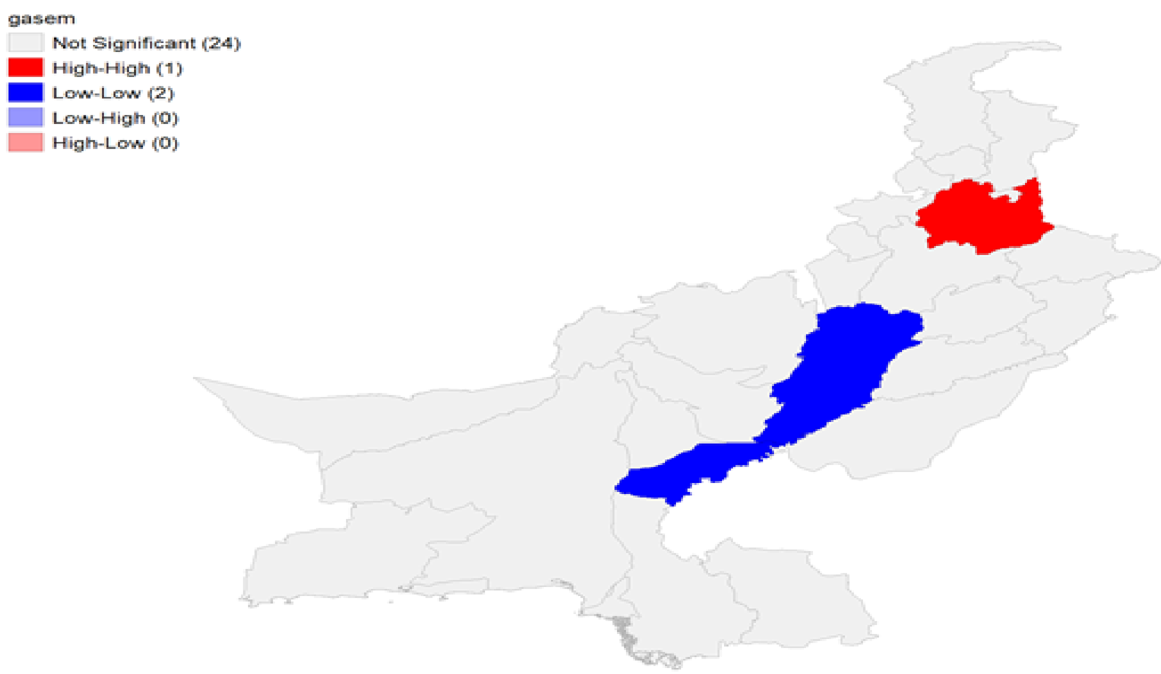


The LISA clustering map indicates low clustering in areas like SIbbi, Larkana and Dera Ghazi Khan divisions. One possible explanation for this clustering is that there may be low availability of LPG infrastructure or low-income levels along with the availability of other cooking fuels. The data demonstrates the LPG consumption and emissions disparities throughout Pakistan's provinces. Encouraging LPG as a cleaner cooking fuel can help reduce home emissions and improve overall environmental quality. Policymakers may utilize this data to tailor actions and promote the use of LPG, contributing to long-term development and environmental preservation. Pakistan can develop towards a more ecologically friendly and healthier cooking landscape by concentrating on clean cooking solutions and spreading knowledge about the benefits of LPG.

4.2.6.5 Households pipeline gas emissions.

The LISA map for household gas emissions, given in Figure 4.6 , indicates high clustering at Rawalpindi and low clustering at the Larkana and Dera Ghazi Khan divisions. High clustering in the Rawalpindi division suggests a concentrated area with high household carbon emissions from pipeline gas. It implies that the Rawalpindi division and its surrounding areas rely more on natural gas as cooking fuel than neighbouring divisions. Possible reasons for this could include urbanisation, industrialization, or greater availability and accessibility of natural gas infrastructure in the Rawalpindi division, leading to increased household usage. Conversely, identifying low clustering in the Larkana and Dera Ghazi Khan divisions indicates regions with consistently low household carbon emissions from natural gas. This spatial pattern suggests a lower reliance on natural gas as a cooking fuel among households in these areas, possibly due to limited access to natural gas infrastructure, economic constraints, or cultural preferences favouring alternative fuels.

Figure 4.6: LISA map of pipeline gas emissions



4.2.6.6 Mix Fuel Consumption

A complex interplay of socioeconomic, environmental and technological factors characterises rural Pakistan's energy landscape. With a significant population residing in rural areas, reliance on traditional cooking fuels is a major pressing issue. The transistion to mix fuel system represents a concept of fuel switching. The study used household survey data regression analysis to delve deeper into the dynamics of fuel switching for energy access and its implications. Table 4.16 summarises the regression results of three key models.

Table 4.16 : Comparison of fuel expenditure

Factors	**Model 1 Single fuel**	**Model 2 Two fuels**	**Model 3 Three fuel**
Female head	0.190 (0.019)	-0.051 (0.035)	-0.009 (0.019)
Educated head	0.017 (0.014)	-0.214*** (0.021)	0.006 (0.011)
Dependent	-0.109*** (0.003)	-0.046*** (0.005)	0.011*** (0.003)
Cooking range ownership	-0.042 (0.127)	-0.757*** (0.151)	0.002 (0.082)
Stove Owned	-0.127*** (0.017)	-0.954*** (0.025)	0.190*** (0.014)
Fire Price	-0.789*** (0.045)	-0.664*** (0.082)	-0.707*** (0.045)
Dung Cake price	-	-	0.154*** (0.013)
LPG price	-	0.201*** (0.024)	2.663*** (0.148)
Household Expenditure	-0.022*** (0.010)	-0.152*** (0.018)	0.386*** (0.010)
Paid firewood	0.606*** (0.015)	0.132*** (0.023)	0.019 (0.013)
Number of fuels		2.760*** (0.028)	0.606*** (0.015)
KPK	0.060* (0.025)	0.421*** (0.045)	0.060* (0.025)
Punjab	-0.052* (0.023)	0.482*** (0.041)	-0.052* (0.023)
Sindh	-0.753*** (0.022)	-0.351*** (0.040)	-0.753*** (0.022)
Constant	-11.215 *** (0.727)	-6.218*** (1.336)	-11.215 *** (0.727)
Model Statistics			
Observations	10636	13875	13875
R sq	0.27	0.58	0.42

Coefficients are reported with standard errors in parentheses. *= p <0.1, ** = p <0.05, *** = p <0.0
Source: Estimated using 2018-19 HIES data.

Model 1 provides valuable insights into the determinants of fuel choice and consumption patterns in households relying on a single fuel source in Pakistan. In Model 1, we explored the characteristics of households reliant on a single fuel source, predominantly traditional biomass fuels like wood or dung, in rural Pakistan. The regression analysis unveiled several critical insights into the factors shaping these households' fuel choice and consumption patterns. Firstly, we observed a significant positive correlation between "female_head" and fuel usage, indicating that households led by females tend to consume more fuel. This finding underscores the disproportionate burden placed on women in energy-intensive activities such as cooking and heating, highlighting the need for gender-sensitive approaches in energy policy and interventions. Secondly, the variable "dependent" exhibited a negative coefficient, suggesting that larger households with more dependents tend to consume less fuel. This could be attributed to economies of scale in fuel usage, where shared resources and efficient cooking practices lead to lower overall consumption.

Moreover, regional disparities played a notable role, with households in Khyber Pakhtunkhwa province showing higher fuel consumption than the reference category. Understanding these regional variations is essential for designing context-specific energy interventions tailored to rural communities' unique needs and preferences. Additionally, the ownership of cooking stoves emerged as a significant factor, with households owning stoves demonstrating lower fuel consumption. This underscores the importance of promoting improved cooking technologies to enhance energy efficiency and reduce reliance on traditional biomass fuels. Overall, Model 1 sheds light on the complex interplay of socio-economic, demographic, and regional factors influencing fuel choice and consumption patterns in single-fuel households, offering valuable insights for developing targeted energy policies and initiatives to promote sustainable energy practices and improve livelihoods in Pakistan.

In Model 2, which focuses on households utilizing a combination of two fuel sources, such as biomass alongside LPG or biogas, we uncover dynamics in fuel choice and consumption patterns within rural Pakistan. Unlike the findings from Model 1, the significance of variables such as female and number of dependants diminishes, indicating that their influence on fuel choice may be less pronounced in households utilizing multiple fuels. This suggests that factors other than household composition play a more significant role in shaping fuel selection when households have access to diverse energy sources.

However, the variable stove ownership remains a significant and positive predictor of fuel consumption, underscoring the importance of stove ownership in reducing overall fuel usage, regardless of the fuel combination employed. Moreover, the introduction of modern energy sources like LPG and biogas, as indicated by the positive coefficients for a log of prices of LPG and Dungcake, respectively, significantly impacts fuel consumption. This highlights the pivotal role of transitioning to cleaner and more efficient cooking technologies in driving fuel consumption patterns towards sustainability and aligning with broader energy transition goals. In summary, Model 2 provides crucial insights into the shifting dynamics of fuel choice and household consumption patterns utilizing traditional and modern energy sources in rural Pakistan. The analysis of the number of fuel variables across the three models yields valuable insights into the impact of fuel diversity on energy consumption patterns in rural households. In Model 1, focused on single-fuel households, the absence of the number of fuels coefficient suggests consistent energy consumption regardless of the number of fuels utilized.

However, in both Model 2 and Model 3, where households use multiple fuel sources, a positive coefficient for the number of fuels used indicates that energy consumption also rises as the number of fuels increases. This suggests that introducing additional fuel sources leads to higher energy demands, potentially driven by diverse cooking needs or preferences. These findings underscore the importance of fuel mixtures in energy planning, highlighting the need for tailored strategies to promote sustainable energy practices and improve energy access in rural areas, particularly as households transition towards mixed-fuel energy systems.

4.2.7 Econometric analysis of Fuel substitution:

The weight shares of the three fuels in the dataset show that, on average, firewood accounts for the most significant amount of overall consumption or expenditure, at around 50.9 percent. Dung cake follows, accounting for around 18.6 percent of the total, while LPG contributes approximately 30.6 percent, as shown in Table 4.17.

Table 4.17: Weight share of fuels

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weight share fire	431	0.508	0.173	0.017	0.925
Weight share Dungcake	431	0.185	0.117	0.0251	0.664
Weight share Lpg	431	0.305	0.159	0.0322	0.790

Source: Estimated using 2018-19 HIES data.

The **Table 4.18** shows parameter estimates from an Almost Ideal Demand System (AIDS) model, which examines the consumption patterns of three types of fuel: firewood, dung cake, and LPG (liquefied petroleum gas). The model has been linearized using the Stone price index. These estimates illustrate how different factors influence the demand for each fuel type. The negative coefficient of firewood indicates that a 1 per cent increase in the price will lead to a decrease in its budget share. This indicates that firewood is considered an inferior good, meaning that households tend to allocate a smaller portion of their budget to firewood consumption as its price rises. The positive coefficient for LPG indicates that households allocate more of their budget to firewood usage when the price rises. As the price of LPG increases, households allocate more of their budget to firewood usage, opting for the cheaper option. This suggests that households are responsive to price changes and adjust their fuel consumption choices accordingly. This implies a substitution effect between LPG and firewood, in which increasing LPG expenditures increase dependence on firewood as a cheaper option.

The negative coefficient for educated households suggests that as education levels rise, the proportion of the budget spent on firewood declines. The negative coefficient for educated households suggests that as education levels rise, the proportion of the budget spent on firewood declines. This could be attributed to increased awareness of alternative energy sources or more efficient cooking technologies among educated households. The coefficient of rural households indicates that rural households spend more money on firewood than urban ones. This positive coefficient suggests that rural families spend more on firewood, which may represent a more significant dependence on fuel for warmth or cooking. The positive coefficient for the KP (Khyber Pakhtunkhwa) province, with a value of 0.0394, indicates that households in KP spend more of their budget on firewood than those in Punjab. These findings highlight the complex dynamics influencing household fuel consumption decisions, including price sensitivity, substitution effects, socioeconomic factors, and regional variations. Understanding these factors is crucial for designing effective energy policies and interventions to promote sustainable fuel use and improve household energy access.

The results for dung cake exhibit similar patterns to those observed for firewood. The positive coefficient for firewood price suggests that as the price of firewood increases, dung cake budget share also rises. This indicates that households may substitute dung cake for other fuels when its price becomes more favourable. Conversely, the negative coefficient for LPG price implies a substitution effect, where higher LPG prices lead to increased reliance on dung cake as a cheaper alternative. Furthermore, the negative coefficient for educated households indicates that higher education levels are related to a smaller share of the budget spent on dung cake, possibly due to an increased understanding of alternate energy sources. The positive coefficient for rural dwellings suggests that they rely more on dung cake than urban households, possibly due to restricted access to other fuels in remote regions. Finally, the positive coefficient for the KP province indicates a regional difference, with households in Khyber Pakhtunkhwa spending a more significant portion of their budget on dung cake than those in Punjab. These findings highlight the complex nature of fuel choice and expenditure patterns, which are impacted by fuel prices, household characteristics, and regional dynamics.

The LPG weight share results also Explain the relationship between fuel prices and consumer behavior. The positive coefficient indicates that as the price of firewood increases, households tend to allocate a larger share of their budget to LPG, suggesting a substitution effect where higher firewood prices lead to increased reliance on LPG as a more affordable alternative. Conversely, the negative coefficient suggests that higher dung cake prices may prompt households to allocate less of their budget to LPG, possibly due to dung cake being perceived as cheaper. Similarly, the negative coefficient for LPG price implies that higher prices lead to a reduced share of the budget allocated to LPG, potentially because households seek cheaper alternatives. The coefficient for education shows a significant relationship, indicating that households with higher levels of education spend a more significant share of their budget on LPG. This positive correlation indicates that education may be linked to a preference for cleaner and more convenient fuel sources like LPG.

Table 4.18: Parameter estimates of AIDS model (linearised with stone price index)

Variables	Firewood	Dung cake	LPG
Price of firewood	-0.239*** (0.056)	0.1318** (0.041)	0.1081** (0.054)
Price of dung cake	-0.060 (0.059)	-0.1482** (0.043)	-0.0877 (0.058)
Price of LPG	0.165*** (0.035)	-0.0824** (0.026)	-0.0832* (0.035)
Fuel expenditure	-0.017 (0.014)	0.0109 (0.011)	0.0064 (0.014)
Educated	-0.073*** (0.015)	0.0074 (0.011)	0.0658*** (0.014)
Rural	0.079* (0.026)	-0.0125 (0.019)	-0.0670* (0.026)
KP	0.079 (0.026)	-0.0031 (0.018)	-0.0363 (0.024)
Constant	1.1550** (0.338)	-0.8384*** (0.251)	0.6834** (0.332)
No. observations	431	431	431
R square	0.24	0.19	0.14

Since the price elasticity of cooking fuel is less than unity, it is anticipated that the increase in price due to a shift in the demand curve will only result in a decrease in the demand by less than proportional change. Firewood and dung cake have a positive cross-price elasticity of 0.00292, which means that a 1 percent rise in the price of firewood results in a 0.292 percent increase in demand for dung cake and vice versa, as shown in **Table 4.19**. This suggests that firewood and dung cake are substitutes, as increasing the price of one causes an increase in demand for the other. With a negative cross-price elasticity of -0.002, a 1 percent rise in firewood prices results in a 0.22 percent drop in LPG demand. This shows a substitution effect between firewood and LPG, in which higher firewood costs reduce demand for LPG, and vice versa. Dung cake and LPG have a negative cross-price elasticity of -0.002, which means that a 1 percent rise in the price of dung cake causes a 0.209 percent drop in demand for LPG and vice versa. This implies that dung cake and LPG are likewise substitutes, with an increase in the price of one increasing demand for the other.

Table 4.19: Own and Cross-Price Elasticities

Elasticity Type	**Firewood**	**Dung**	**LPG**
Own-Price Elasticity	-0.000735	-0.00413	0.0024
Cross-PriceElasticity (Firewood-Dung)	-	0.00292	-
Cross-PriceElasticity (Firewood-LPG)	-	-	-0.00228
Cross-Price Elasticity (Dung-LPG)	-	-	-0.00209

4.2.8 Household Food Consumption:

To analyze the household's own price and cross elasticities, the study employed the linear approximation of l (AIDS). This model was conducted for six commodity groups: cereals, pulses, milk, meat, fruits, and vegetables. The dataset encompasses a sample size of 24,809 households due to miss. However, on the quantities of various commodities consumed and expenditures made by some households, the analysis was conducted using data from 24,620 households. The descriptive statistics in Table 4.20 revealed patterns of Pakistani households towards eight food commodity groups, their respective prices, and household age composition. Notably, households allocate significant portions of their incomes to milk (31%) and cereals (23%), followed by expenditures on meat (13%), vegetables (11%), fruits (0.05%), and pulses (0.03%). Variations in budget shares across commodity groups indicate the highest variability in meat expenditure (69%) and the lowest in cereals (35%). Regarding prices, households typically pay higher prices for meat (PKR313/kg) and pulses (PKR134/kg), while prices are comparatively lower for fruits (PKR94/kg), milk (PKR85/kg), cereals (PKR41/kg), and vegetables (PKR40/kg). The coefficient of price variations ranges from 0.09 to 0price variations observed for cereals (34%) and the lowest for fruits (9%).

Table 4.20: Descriptive statistics for Household Food consumption (kg/ month per household)

Variable	Mean	Standard deviation
Cereals	0.23	0.08
Pulses	0.03	0.02
Milk	0.31	0.12
Meat	0.13	0.09
Fruit	0.05	0.03
Vegetables	0.11	0.04
Food prices		
Cereals price	50	15.1
Pulses	134	18.2
Cereals	85	19.1
Meat	313	107.4
Fruit	94	31.2
Vegetables	40	9.6

Source: author's calculation based on HIES 2018-19

4.2.8.1 Results of 'LA/AIDS model

The results for households for the consumption of LA/AIDS are given in the Table 4.21.

Table 4.21: Results of LA/AIDS model for Household Food Consumption expenditure

Variables	**Cereals**	**Pulses**	**Dairy**	**Fruit**	**Vegetables**
Price of Cereals	0.019^{***} (0.001)	0.029^{***} (0.0002)	-0.0114^{**} (0.001)	0.0028^{***} (0.000)	-0.0106^{***} (0.000)
Price of pulses	0.0169^{***} (0.0026)	0.019^{***} (0.00)	-0.004 (0.004)	-0.005^{***} (0.001)	0.0085^{***} (0.001)
Price of dairy	-0.018^{***} (0.026)	0.011^{**} (0.001)	-0.022^{***} (0.002)	-0.003^{***} (0.000)	0.0016 (0.001)
Prices of fruit	-0.0211^{***} (0.0013)	-0.001^{***} (0.00)	0.0018 (0.001)	0.023^{***} (0.00)	-0.008^{***} (0.000)
Prices of vegetables	-0.039^{***} (0.002)	0.0012^{***} (0.011)	-0.051^{***} (0.002)	0.0158^{***} (0.000)	0.063^{***} (0.001)
Children (Age≤19)	0.019 (0.000)	-0.000 (0.018)	-0.021^{***} (0.001)	-0.0049^{***} (0.000)	0.0039^{***} (0.000)
Adult (20≤39)	0.008^{***} (0.001)	-0.0059^{***} (0.002)	0.0039 (0.002)	0.0019^{***} (0.000)	-0.002^{***} (0.000)
Middle age(40≤59)	0.016^{***} (0.000)	0.0019^{***} (0.000)	-0.0041^{***} (0.0012)	-0.0039^{***} (0.000)	-0.0021^{***} (0.000)
Elders (age≥60)	0.0081^{***} (0.001)	-0.000 (0.001)	0.0068^{***} (0.001)	-0.0019^{***} (0.000)	-0.0056^{***} (0.000)
Constant	2.01^{***} (0.028)	-0.0689^{***} (0.0049)	-0.057*** (0.029)	-0.16^{***} (0.011)	0.195^{***} (0.011)
No. observations	24,000	24,000	24,000	24,000	24,000
R square	0.24	0.19	0.49	0.21	0.11

Source: Estimates using HIES 2018-19

The income/expenditure elasticities are presented in Table 4.22. The analysis demonstrates that the expenditure elasticities for dairy and fruits surpass one, signifying their classification as luxury items for households. This implies that with an increase in household income, there is a corresponding rise in the consumption of these food items. This association underscores the discretionary nature of these products, with consumption patterns intricately tied to the household's financial well-being. These findings align with the previous research that indicates milk, meat and fruits as luxury food items Ullah et al. (2018). Similarly, a study by Akram identified that beef, mutton, chicken, seafood and dry fruits are income elastic, while milk and yoghurt are relatively income inelastic. Hameed and Salman (2017) and Hina et al. (2010) categorized meat and fruits as luxury items, contrasting with dairy products as necessities. In contrast, cereals, pulses and vegetables, exhibit income elasticities less than one, indicating them as necessities.

This suggests that as household expenditure increases, the consumption of pulses, cereals, and vegetables increases because of the staple nature of these commodities. The observed phenomenon of increased demand for cereals and pulses with rising prices aligns with the concept of inelastic demand, where consumers continue to purchase essential goods regardless of price changes. This behavior is well-documented in economic literature. For example, studies by Gostkowski (2018) and Türkmen-Ceylan (2019) have explored the effects of price variations on food consumption patterns, highlighting instances where certain food items exhibit inelastic demand, leading to increased consumption even with price hikes. These findings provide theoretical support for th. e results obtained in the LA/AIDS model for food consumption, indicating a consistent pattern of consumer behavior in response to price fluctuations. These findings are consistent with various research studies.

The research study by Ullah et al. (2018) and Hamed and Salman (2021) identified wheat flour, pulses, vegetables and oils as essential food items. According to that study, rice and cereals were considered luxury items, implying that their consumption does not significantly increase with income growth, meaning that their consumption remains relatively stable regardless of income changes. In contrast, sugar displayed income elasticity, indicating a more pronounced increase in consumption with rising incomes. Conversely, Haider and Zaidi (2017) categorized pulses as essential items while wheat pulses, oil and vegetables as luxury items. The compensated own-price elasticities from Table indicate that inelastic responses to price changes characterise the food commodity groups. These items are considered essential or integral to the household diet, as price fluctuations do not significantly alter their consumption levels. These findings are consistent with prior studies by Ullah et al. (2018), Hameed and Salim (2017), and Hayat et al. (2023), which have identified wheat and wheat flour, rice, other cereals, milk, meat, fruits, pulses, vegetables, sugar, and oil and fats as staple food items. It implies that when these food items become more expensive, people generally buy them because they are necessary for their diet. This is different from the goods with elastic demand.

Table 4.22: Compensated own and Cross-Price Elasticity

Food Group	Cereals	Pulses	Dairy	Meat	Fruits	Vegetables
Cereals	-0.589	0.0391	0.194	0.206	0.0498	0.0495
Pulses	0.912	-0.0798	-0.895	-0.597	-0.159	0.39
Dairy	0.208	0.0596	-0.854	0.219	0.0432	0.192
Meat	-0.160	-0.0234	-0.210	0.0860	0.0196	-0.0769
Fruits	-0.301	-0.00291	0.291	0.214	-0.495	-0.0112
Vegetables	0.694	0.043	-0.149	0.021	0.21	-0.294

Source: Estimates using HIES 2018-19

The findings from the study on compensated cross-price elasticities highlight significant instances of gross substitutes among various food commodity groups in Pakistani households. Specifically, cereals exhibit a substitutive relationship with both pulses and vegetables. This implies that when cereal prices increase, households tend to adjust their consumption by favouring pulses or vegetables as substitutes, and vice versa when cereal prices decrease. Pulses, cereals, and vegetables are essential staple foods in Pakistani households, providing vital nutrients like protein, vitamins, and minerals. Therefore, households adapt their consumption between these items in response to price changes. In Pakistan, Pulses, cereals, and vegetables play pivotal roles as staple foods, offering essential nutrients such as protein, vitamins, and minerals.

Therefore, households consume these food items in response to changes in their relative prices. Similarly, an evident substitutive relationship holds between pulses and vegetables indicating interchange one for another in response to price changes. In Pakistan, the phenomenon is evident that households with limited purchasing power heavily depend on economical foods like vegetables and pulses. The recent surge in pulse prices within Pakistan has prompted households to adjust their consumption patterns, favouring increased intake of vegetables and cereals as a more cost-effective alternative. Similarly, when the prices of dairy products increase, the consumption of cereals, meat, and vegetables increases, implying that dairy products are substituted with cereals, meat, and vegetables. It is also observed that when the price of fruits increases, the consumption of dairy products increases—implying that households are substituting fruits with dairy products as a cheaper source of nutrition.

However, when the price of vegetables increases, the consumption of cereals increases, indicating that substitution occurs between vegetables and cereals.

The study findings align with Hayat et al. (2023) in observing substitution patterns among different food commodity groups in Pakistani households. Specifically, both studies highlight the significant impact of prices on food consumption patterns, indicating that as prices of pulses, meat, dairy, and vegetables increase, households tend to adjust their consumption patterns. This adjustment leads to a shift towards increased consumption of cereals, which are likely perceived as more affordable alternatives when prices of other food items rise. This consistency in findings underscores the importance of price elasticity and substitution effects in shaping household food consumption behavior.

On the other hand, it contradicts Ullah et al. (2018) and Akram (2020) regarding the specific substitution patterns observed among food commodity groups. While Hayat et al. (2023) suggest a substitutive relationship between dairy, meat, fruits, and cereals, Ullah et al. (2018) and Akram (2020) may have reported different or conflicting substitution patterns in their studies. These findings could be due to methodological differences, the periods covered, the specific regions or populations studied, or the data sources employed.

Furthermore, the study findings indicate that with rising household income, there is an increased demand for milk, meat, and fruits, reflecting the income elasticity of these food items in Pakistani households. This aligns with the concept of income elasticity, where certain food items are considered luxury goods that experience a more significant increase in demand as household income rises. Understanding income elasticity is crucial for policymakers and researchers to comprehend how changes in income levels influence food consumption patterns and preferences among households.

In summary, while the study is consistent with Hayat et al. (2023) in terms of observing the impact of prices on food consumption patterns and income elasticity, it may differ from Ullah et al. (2018) and Akram (2020) in terms of specific substitution patterns identified among food commodity groups. These discrepancies highlight the complexity of household food consumption behavior and the importance of considering various factors influencing consumption decisions. This analysis indicates that food consumption patterns heavily depend on prices. Suggests that the prices of pulses, dairy, and vegetables increase in the household consumption pattern and have a significant shift in food consumption patterns, mainly increasing the consumption of cereals. Similarly, as household income increases, there is a significant increase in demand for milk, meat, and fruits.

4.2.8.2 Integrating food elasticities and food emissions

The study's insights on food consumption patterns, emissions, and elasticities offer a valuable understanding of how dietary choices, environmental impact, and consumer behavior intersect. By combining these findings with existing research, compelling support can be established for advocating sustainable food consumption practices. This synthesis forms a robust foundation for promoting environmentally conscious dietary habits. By analyzing food emissions data, the study reveals the varying environmental effects of different foods. Notably, mutton, rice, and milk are identified as high-emission foods, underscoring the importance of reducing consumption of these items to mitigate their environmental footprint. For instance, mutton stands out for its significant emissions contribution, highlighting the need for decreased consumption to lessen environmental harm. In contrast, leafy vegetables and fruits exhibit lower pollution levels, suggesting their potential as environmentally friendly alternatives.

Furthermore, examining food elasticities sheds light on how price changes influence consumer demand and behavior. The analysis reveals that vegetables and pulses act as gross substitutes, indicating that households may increase vegetable consumption as pulse prices rise. Similarly, a substitutive relationship is observed between meat and fruits, suggesting that as meat prices increase, households may opt for more fruits and vice versa.

By integrating food emissions and elasticities knowledge, policymakers can design targeted interventions to encourage sustainable food choices. Strategies such as promoting plant-based alternatives for high-emission foods and implementing pricing mechanisms that align with emission reduction goals can be effective in fostering ecologically conscious consumption patterns. This holistic approach supports evidence-based decision-making and facilitates the adoption of sustainable practices in food consumption.

The present study observed that an increase in the price of pulses led to an increase in the consumption of vegetables, indicating a substitutive relationship between these two food commodity groups in Pakistani households. This finding suggests that households tend to substitute pulses with vegetables when pulse prices rise, possibly due to the relative affordability and availability of vegetables as an alternative source of nutrition.

Moreover, the study also noted that when vegetable prices increase, the consumption of cereals and fruits increases. This observation implies a complementary relationship between vegetables and cereals/fruits, where households may opt for cereals and fruits as substitutes for vegetables when vegetable prices become less favourable. This shift in consumption patterns highlights the intricate dynamics of food choices influenced by price changes within different food groups.

These findings are consistent with substitution and complementarity effects in food consumption patterns, as observed in various studies. For instance, research by Gostkowski (2018) on consumer demand elasticity using an almost ideal demand system also emphasizes the importance of understanding how households substitute or complement different food items in response to price fluctuations. Similarly, Türkmen-Ceylan (2019) explored the impact of economic crises on consumption patterns and identified instances of substitution between food groups in Turkey.

By considering the interplay of price changes and consumption behaviors across food commodity groups, the study by Hayat et al. (2023) contributes to the broader literature on household food consumption patterns. It highlights the nuanced relationships that exist among different food items. Understanding these substitution and complementarity effects is essential for policymakers and researchers to design effective strategies that promote food security and address changing dietary preferences in diverse populations.

4.2.8.3 Mitigation Strategies:

Based on the empirical findings, effective decarbonization requires a blend of technology adoption, economic incentives, and behavioral interventions. The following strategies are targeted at the largest components of household emissions: cooking fuel, electricity, and food consumption.Understanding the contribution to home emissions is critical for progress towards a low-carbon future. Although many elements of the urban household energy system, from power to transportation and cooking, lead to CO_2 emissions, electricity appears to make a significant contribution. However, it is essential to note that the carbon footprint of urban houses comprises not only energy usage but also daily habits and routines. Decarbonization targets will require a different energy supply mix, along with changes in urban family consumption patterns and daily habits. It includes elements such as lifestyle factors, physical housing characteristics (such as geography and size), socio-economic factors that affect households, as well as local policies.

4.2.8.4 Cooking fuel consumption:

The transition away from high-emission solid cooking fuels (e.g., firewood, dung cake) is crucial for both mitigation and public health adaptation. Strategies must address the three key barriers: affordability, infrastructure, and behavioral inertia.

Subsidized Clean Fuel Access and Infrastructure:

The primary intervention must be a sustained, long-term policy of subsidizing the initial capital cost of clean cooking equipment stoves, induction cooktops, or certified Improved Cook Stoves (ICS) for low-income households, coupled with reliable fuel delivery infrastructure. Subsidies should also target the recurring cost of cleaner fuels like to ensure continuous use, preventing households from stacking clean fuels with traditional, cheaper biomass (Pachauri et al., 2021).

Promoting Decentralized Biogas Systems: In rural and peri-urban areas, promote the adoption of household- or community-level biogas digesters that convert organic waste (including dung cake) into methane for cooking (Lam et al.,2012). This achieves a dual mitigation benefit by displacing solid fuel use and reducing methane emissions from decomposing waste.

Time Poverty Reduction and Gender Adaptation: A crucial adaptation benefit for female-headed households is the reduction of time poverty (Clancy & Skutsch.,2015). Switching from firewood/dung cake (which requires time-consuming collection and monitoring) to or piped gas frees up substantial time for women and children, allowing for greater participation in education or income-generating activities.

4.2.8.4.1 Electricity and Energy Consumption:

To mitigate emissions from household electricity consumption, strategies must focus on both mandating higher efficiency standards and using behavioral economics to influence daily usage.

Governments should enforce Mandatory Minimum Energy Performance Standards (MEPS) for appliances to systematically remove inefficient products from the market. This structural change must be supplemented by implementing a clear, standardized "lifetime carbon footprint" labeling system on all major appliances to allow consumers to factor the full environmental cost into their purchasing decisions. To influence daily consumption habits, utilities should regularly send consumers personalized, comparative feedback on their electricity use, benchmarking their consumption against that of similar, high-performing neighbors. This strategy leverages the power of social norms and has been empirically proven to significantly reduce consumption more effectively than generic appeals to conserve energy (Allcott, 2011).

4.2.8.4.2 Behavioral Modifications:

Behavioral strategies provide a cost-effective means of reducing emissions by influencing everyday decision-making through behavioral economics. Social norm nudges, such as personalized comparative feedback, encourage households to lower energy use by comparing their consumption with that of efficient neighbors (Allcott, 2011). Another effective approach is the default bias or opt-out system, where sustainable options (e.g., green energy tariffs) are set as the default choice. This "choice architecture" leverages human inertia to promote cleaner behaviors with minimal resistance (Pichert & Katsikopoulos, 2008; Thaler & Sunstein, 2009).

4.2.8.4.3 Food Consumption:

Addressing the large carbon footprint associated with food consumption requires strategies that integrate public health messaging with systemic changes to the food economy.Public awareness campaigns must link the health benefits of adopting plant-rich diets (fruits, vegetables, and grains) with their substantially lower emissions profiles compared to high-emission animal products, particularly red meat. This dual messaging appeals to both individual health and collective climate benefit (Hoolohan et al., 2013; Poore & Nemecek, 2018). Simultaneously, adaptation and resilience strategies require policy support for community-supported agriculture (CSA) and local market linkages to reduce supply chain emissions and strengthen local food systems against external shocks. Finally, a key mitigation strategy involves tackling waste through the institution of mandatory residential composting programs with coordinated municipal collection. This measure directly targets the emissions (methane) generated by food waste in landfills, representing a crucial opportunity for urban decarbonization.Government agencies, non-governmental organizations, companies, and local communities must work together to implement these policies. It is imperative to customise these tactics to the unique requirements and capabilities of diverse locations in Pakistan, all the while guaranteeing inclusion and practicality for homes from a range of socioeconomic backgrounds. It will be essential to conduct routine monitoring and assessment to determine these policies and make any required modifications.

Chapter 5

REVIEW OF POLICIES

5.1 Introduction

The impact of environmental variation on the Earth's climate can be seen through the increased concentration of greenhouse gases (GHGs), particularly carbon dioxide (CO2), contributing to global warming. Greenhouse gases (GHGs) encompass a variety of compounds, such as methane, nitrous oxides, carbon dioxide (CO_2), ozone, and water evaporation. The carbon dioxide emissions from individual actions stem from burning fossil fuels and activities such as soil erosion, deforestation, animal husbandry, and agriculture The adverse impacts of greenhouse gas (GHG) emissions are increasing, the prevalence of dense smog in various metropolitan cities worldwide for several months annually, such as in China (Kaur, 2022; Zhang et al., 2010), along with the resultant increase in healthcare expenses due to hazardous emissions, as well as the occurrence of catastrophic droughts and floods have emerged as challenging obstacles to the prosperity and economic development globally. The power sector was attributed to the emission of global greenhouse gases in the year 2014. The International Energy Agency (IEA) 2017 reported that CO_2 accounts for 90%, N_2O for 1%, CH4 for 9%, and other gases for 14% of the total omissions. According to Sargani et al. (2022), climate change impacts various aspects such as weather patterns, household income, poverty levels, agricultural and forest products, local livelihoods, and crop yields.

Due to the Arctic sea ice is melting at a rate of 2.7% per decade, the global average temperature has increased by 0.74°C since 1961, and the sea level is rising at a rate of 1.8 mm per year. For the 21st century, the IPCC forecasts a temperature increase of 1.5 to 8.8°C. Himalayan mountain glaciers are melting faster than ever in recorded history (Bannari & Al-Ali, 2020). CO2 levels are about 28–29% higher today than 150 years ago. According to ice core data, the CO2 level has not increased in the last 420,000 years (Song, 2023). Carbon concentration has increased from 760 GT in 2001 to 1000 GT over the last 15 years due to the rapid rise in CO2 emissions (40 Gt CO2/y). The atmosphere's net carbon concentration is rising at 18 GtC per year. This high rate may be attributed to the oversaturation of the oceans and the global acceleration of deforestation (Fennel et al., 2022; Lenton & Britton, 2006). There is growing agreement among agriculture, environment, and energy experts about how climate change affects our daily lives70%. Serious consideration is given to the relationship between population, water, food, energy, poverty, and security (Neacsa et al., 2020).

5.2 Global Demand for Fuel

Energy constitutes a fundamental source for fostering economic development which is widely acknowledged in literature (Zaman et al., 2012). According to (Pérez-Lombard et al., 2009), it is projected that emerging and middle-income economies located in regions such as South America, the Middle East, Africa, and Southeast Asia will exceed the energy consumption of developed countries, including North America, New Zealand, Australia, Western Europe, and Japan by the year 2020. The acceleration in energy demand, particularly from emerging economies coupled with resource scarcity, has resulted in a steady increase in the cost of energy sources (Hadjipaschalis et al., 2009). As a result, there is a growing disparity between the need for and availability of energy sources, particularly in emerging and intermediate economies. The growing need for energy coupled with nations' dependence on scarce energy resources implies that ensuring sufficient energy supply may emerge as a significant global challenge (Ahmad et al., 2020).

The global impact of climate change has become a universal phenomenon, with evident environmental fluctuations spanning multiple decades, necessitating examining the attributes of human-generated carbon dioxide (CO2) emissions, i.e., primary climate change factor. These emissions are primarily produced through coal, oil, and gas combustion, significantly impacting the global climate (Sarkodie & Owusu, 2021).

Over two billion individuals worldwide rely on solid fuels for cooking and heating, including coal, crop residues, firewood, animal dung, and charcoal. Upon burning, solid biomass fuels release various intricate compounds, such as nitrogen oxides, carbon monoxide, cilia contaminants, and other inhalable particulates, which can have detrimental effects on both the environment and human health (Irfan et al., 2017, 2018; Verma et al., 2021). Solid fuels are typically burned in open fires or using stoves with three stones, releasing substantial amounts of harmful chemicals. Indoor air pollution, primarily caused using solid fuels, is caused by the premature deaths of nearly 1.6 million individuals globally yearly. Additionally, numerous individuals suffer from severe diseases such as lung infections, asthma, eye infections, cancer, tuberculosis (TB), and cardiovascular diseases (Guta et al., 2022; Lin & Raza, 2020; Raza & Lin, 2020).

The utilization of solid fuels has a significant impact on human populations and the natural environment. Using wood as a cooking fuel in households has gradually depleted forests in emerging nations. The significance of forests lies in their numerous contributions to the economy, ecology, society, environment, and health, and they offer a range of benefits in mitigating global warming (Creutzig et al., 2015). Despite the negative impact of biomass fuel on the environment and human health, using solid fuels for cooking, lighting, and heating continues to be prevalent in emerging countries, including Pakistan.

Like other middle-income nations, Pakistan relies on various fuel sources for cooking and lighting, including firewood, electricity, crop residues, natural gas, Liquefied Petroleum Gas (LPG), and animal dung. Lighting is typically powered by electricity, while alternative fuels are frequently used for heating and cooking. The utilization of solid fuels, including firewood, dry animal dung, and crop residues, is more prevalent in rural regions compared to their urban counterparts. In contrast, it is observed that using environmentally well-disposed energy sources, for instance, natural gas is less prevalent in rural regions than in their urban counterparts.

5.3 Situating Pakistan on the Canvas

Pakistan's 185 million population is the sixth most populous nation globally. According to a study conducted by (Colbeck et al., 2010a, 2010b), it has been approximated that the number of yearly fatalities caused by acute respiratory illnesses (ARI) in children below the age of five in Pakistan is 51,760. Additionally, there are 18,980 annual deaths attributed to chronic obstructive pulmonary disease (Hassan et al., 2021).

The Islamic Republic of Pakistan, a nation in the development process, is experiencing a surge in its energy requirements and is faced with a persistent challenge in its electricity supply infrastructure. Notably, Pakistan also formally approved the Paris Agreement in 2016. Pakistan is faced with a typical dilemma of achieving the objective of decreasing emissions by 5% below the 2012 levels by 2030, as outlined in Pakistan's Intended Nationally Determined Contributions (INDC) presented in 2016. In 2012, Pakistan's energy sector was responsible for the highest carbon dioxide emissions, comprising 46% of the total emissions of 342 Mt CO_2. In the year 2030, the electricity industry in Pakistan was responsible for emitting an estimated 67.364 million metric tons of carbon dioxide. The power sector in Pakistan is a significant source of environmental emissions, and there is potential for reducing these emissions by implementing alternative measures (Pakistan, 2021)[1].

According to the U.S. Energy Information Administration (EIA), Pakistan's primary energy consumption amounted to 2.54 Quadrillion British Thermal Units (QBTU) in 2011. In 2013, Pakistan's per capita energy consumption was recorded at 475 kg of oil equivalent per annum, putting the country at 133rd in the global ranking.

It is depicted that the aggregate energy usage of households in Pakistan is based on specific energy sources comprising natural gas, LPG, firewood, animal dung, and agricultural waste. The trend in fuel consumption is generally increasing, except for LPG, which could be linked to the rise in natural gas consumption (Baul et al., 2018). In recent years, the energy demand has significantly increased, but due to inadequate policies, this increase has not been caused by poor management. Consequently, power shutdowns are widespread, hindering the country's growth and impacting quality of life (Rao et al., 2022).

The insufficiency of research that sufficiently addresses policy analysis regarding the patterns of carbon omission in Pakistan is significant. Determining reasonable energy prices, subsidies, and taxation levels for solid and clean fuels remains challenging for policymakers responsible for shaping household energy consumption and choices. Previous research has examined Pakistan's fuel and price expenditure elasticities for domestic heating and cooking fuels. However, policymakers are emphasizing peripheral issues instead. According to reports, price inelasticity exists for all fuel types except natural gas, both at the national level and for households residing in urban areas. The price elasticity of natural gas and LPG tends to be higher in rural areas than urban areas. According to our policy simulations, it is recommended that the Pakistani government consider subsidising clean fuels instead of imposing taxes on solid fuels to mitigate indoor air pollution. Furthermore, it is suggested that the government prioritize subsidizing LPG over piped natural gas.

[1] This policy review is using figures reported in Government of Pakistan. (2021). Pakistan: Updated nationally determined contributions 2021. New York: UN Framework Convention on Climate Change.

5.4 Environmental Emissions in Pakistan

Baig et al. (2019) assert that environmental change has significant and immediate effects on various sectors in Pakistan, such as water availability, crop patterns, livestock, forests, biodiversity, and coastal zones. Hence, this represents a highly hazardous and complex ecological concern necessitating mitigating climate change's effects as INDCs. Various nations submitted these contributions to the twenty-first Conference of the Parties (COP21) for climate change in December 2015, and they are crucial in achieving the desired outcome. Pakistan is one of several countries vulnerable to climate change's consequences. Eckstein et al. (2017), Pakistan is consistently impacted by climate change and occurrences of severe weather patterns, which have led to a financial loss of more than US$9.6 billion to Pakistan since 2010, as reported by the Pakistan Climate Public Expenditure and Institutional Review in 2017.

Khan (2014) and Lin and Ahmad (2016) have posited that Pakistan's vision is centered on elevating the country to the top 25 nations in terms of economic growth, increasing energy accessibility to a range of 67% to 90% of the population, and mitigating the effects of climate change. Despite Pakistan's relatively low contribution of 0.8% to global emissions, the Government of Pakistan (GOP) has demonstrated a commitment to addressing climate change through various strategies, including reducing greenhouse gas (GHG) emissions. The primary focus areas include power generation, transportation infrastructure, forestry management, household fuels, urban planning, and manufacturing zones. The origin of INDC can be traced back to Pakistan, as documented by the National Climate Change Policy (NCCP, 2012).

5.5 Climate Posed Challenges

5.5.1 Climatic Impact-Drivers (CIDS)

Changes in weather patterns, including variations in temperature and precipitation, melting glaciers, rising sea levels, a decline in biodiversity, desertification, and droughts, are signs of the inception of climate change in Pakistan. Pakistan has seen an increase in temperature of 0.76 C on average. Still, the rise has been more significant in some areas than the national and global averages. Swat and Chitral, typically outside the monsoon range, are now impacted by the monsoon. The physical environment is negatively impacted, the carrying capacity of ecosystems has been weakened, and urban and rural areas are now more vulnerable to climate-related disasters.

The CIDs are seen in Baluchistan and Sindh's coastal belts as an increase in tropical storm frequency and intensity, coastal rains, and seawater intrusion; however, in Punjab and Sindh planes, that have an impact on agriculture and public health, as well as an increased drought in Baluchistan, Sindh, and Punjab. Human health has been negatively impacted, water agriculture has been negatively impacted, and ecosystem productivity has decreased because of ecosystem degradation.

5.5.2 Compound Extreme Weather Events

The incidence and severity of floods and landslides have resulted in a significant proportion of the country's people being exposed to climatic-related hazards, rendering them susceptible. Complex weather phenomena and the convergence of multiple factors and hazards contribute to risks that affect society and the environment. Simultaneous extreme events have increased across various locations, including mountainous regions such as Karakoram, Himalayas, Hindukush, and agricultural areas producing food. Moreover, Sindh's heat waves have experienced temperatures reaching 52°C, which makes it impossible for humans to endure temperatures exceeding the limit of 52°C. The study indicates that there was a notable increase in mean temperatures across all regions of the country during the period spanning from 1951 to 2000. The geographic regions of Sindh and Gilgit Baltistan (GB), among others, are experiencing an increase in precipitation variability, which is anticipated to have significant consequences for the future of food security in the country.

5.5.3 Socio-Economic Dimensions

Pakistan is estimated to have a population of 225 million, ranking it the fifth-most populous country globally, with a growth rate of 2.4% annually. Pakistan's per capita carbon dioxide equivalent emissions amount to 2.4 tonnes, positioning it at the 19th rank worldwide and the third rank regionally in terms of emissions. According to projections, 338 million by 2025 and 2050 will be under business-as-usual (BAU) conditions. This would result in per capita emissions of 2.9 and 5.4 tonnes of CO_2 equivalent by 2025 and 2050, respectively. Pakistan is characterized by a youthful demographic profile, as evidenced by its projected population of approximately 181 million adults by 2050. This is further supported by an estimated influx of four million individuals entering the workforce annually. Approximately 29.5% of the entire populace resides below the poverty threshold, and the unemployment rate is reportedly at 4.7%.

According to the Ministry of Planning Development & Special Initiatives (MOPD&SI), the COVID-19 pandemic has resulted in significant job losses, with an estimated 12.3 million to 18.5 million unemployed people. Pakistan remains an agrarian economy. The negative consequences of climate change significantly reduce livelihoods, productivity, and the well-being of humans. The agricultural industry relies heavily on water resources, and climate change has emerged as a primary factor contributing to water insecurity, leading to agricultural losses and food insecurity. The updated submission of the Nationally Determined Contribution (NDC) has been formulated with an awareness of the prevailing socioeconomic obstacles presented by the COVID-19 pandemic.

5.5.4 Economic Costs

Preliminary sector-specific analyzes have been conducted to assess the direct financial implications of climate variation. The (NFPP-IV) approaches that the expenses associated with flood calamities have varied between US$3.32 billion annually, contingent upon the frequency and severity of the floods. (UNDP) in 2015, Pakistan reportedly allocated 5.8-7.6% of total expenditures concerning climate change, with approximately 11% dedicated to adaptation and mitigation efforts. In 2016, Pakistan's required adaptation measures were estimated to be US$ 7-14 billion annually until 2050, where 70% is attributed to infrastructure expenses. Policy initiatives refer to the actions taken by governments for mitigation and adaptation, including the following.

5.6 Mitigation and Adaptation Policy Actions

Policy initiatives refer to the actions taken by governments for mitigation and adaptation, including the following. Since submitting the NDC in 2016, (GoP) has implemented various policy measures. Implementing environment-based strategies, carbon sequestration practices, and integrating renewable energy sources has surpassed the discourse presented in the Nationally Determined Contributions. To support its objectives, the Government of the Philippines (GoP) has implemented a Nature-based Solutions (NbS) strategy in conjunction with environmentally friendly job opportunities and other related activities despite the constraints of its limited domestic resources.

The Government of Pakistan (GoP) has announced its objective to adhere to the (GHG) emissions trajectory of 1603 million tons of CO_2 for the year 2030, which was previously determined in the country's initial NDC submission in 2016. Despite the challenges of meeting the GHG emission reduction targets outlined in the Paris Agreement to limit global temperature increases to 1.5-2°C. The GOP has implemented a range of significant measures to achieve a total reduction of 50% in its anticipated emissions by 2030. This goal will entail a 15% reduction below business as usual (BAU) levels, achieved through domestic resources. A further 35% reduction below BAU levels will also be pursued, conditional upon the International Finance Corporation (IFC) provision. The Gop significantly emphasizes reducing greenhouse gas (GHG) emissions in four sectors. However, implementing these initiatives is subject to the availability of IFC.

5.6.1 Mitigation Actions

Pakistan has made progress in its mitigation efforts and has extended its focus on climate change beyond its Nationally Determined Contributions (NDCs). The country has implemented various initiatives that have resulted in an 8.7% reduction in emissions between 2016 and 2018.

5.6.1.1 Energy Demand and Supply Management:

The country is currently experiencing a demand-supply gap of 3000 Mega Watt (MW), which can be efficiently mitigated through improvements in the energy mix. The National Electric Vehicles Policy 2020-25 (NEVP 2019) has been sanctioned by GoP to enable demand-side management.

5.6.1.2 Engaging Private Sector

The Government of Pakistan (GoP) has initiated the involvement of the private sector in the provision of energy supply. In 2019, a Result Based Financing (RBF) pilot project was launched in Sindh and Punjab to incentivise private sector investment in off-grid solutions based on the International Finance Corporation's (IFC) standard products for off-grid communities.

5.6.1.3 Coal Consumption Trends

Over the past five years, there has been a threefold increase in coal consumption in Pakistan, reaching 21.5 million tonnes per year. This rise in demand can be attributed to industrial growth and the initiation of coal power plant construction in 2018. Over the past five years, there has been a significant increase in coal imports, with a five-fold rise observed. This trend is attributed to industrial purposes, accounting for approximately 73% of the total coal imports. Notably, the cement sector is the primary consumer of industrial coal, representing

65% of the overall industrial coal consumption. The notable economic expansion observed until 2018 resulted in a surge in cement manufacturing, pushing the projected growth of cement production to an annual rate of 10-15% over the upcoming decade by 2030. According to the data, the proportion of power generation derived from coal was 24% during the fiscal year 2021. It is projected to rise to 31% by the fiscal year 2025, owing to the establishment of committed plants. However, it is anticipated to decline to 20.1% by the fiscal year 2030.

5.6.1.4 Energy Mix Projections

Energy mix projections refer to the anticipated distribution of various sources of energy that will be used to meet the energy demands of a particular region or country over a specified period. Pakistan has a projected hydropower capacity of roughly 60,000 megawatts (MW), with a current utilization rate of approximately 14%. Pakistan possesses (solar PV) on average, distributed across a small portion of the country’s land, primarily located in the Balochistan province. The coastal regions of Sindh and Balochistan in Pakistan present a significant opportunity for generating wind power, which remains largely unexplored. In recent years, there has been a notable increase in the proportion of renewable energy sources, rising from 0.25% in 2015 to 5% in 2018.

5.6.1.5 Renewable Energy

According to projections, renewable energy sources, such as hydro power, are expected to account for 60% of the total energy production in the country by the year 2030.

5.6.1.6 Transportation

According to projections, a significant proportion of newly purchased vehicles across different categories in Pakistan will be Electric Vehicles (EVs) by 2030, accounting for approximately 30% of total sales.

5.6.1.7 Forestry & Change in Land-Use

The Ten Billion Tree Tsunami Programme (TBTTP), the country's largest-ever afforestation initiative, will continue investing in NbS from 2016 onward, capturing 148.76 MtCOe emissions over the preceding ten years. A total contribution of US$800 million is estimated to meet the objective.

1. **Policy Environment**: The policy environment in Pakistan acknowledges the crucial role of the energy sector in achieving mitigation targets. Pakistan has instituted several policies. The policies above are under the management and direction of regulatory

bodies and specialized agencies, including but not limited to the National Electric Power Regulatory Authority (NEPRA), Central Power Purchasing Agency Guarantees (CPPA-G), Alternative Energy Development Board (AEDB), Water & Power Development Authority (WAPDA), National Transmission & Dispatch Company (NTDC), Pakistan Atomic Energy Commission (PAEC), Private Power & Infrastructure Board (PPIB),.

2. **Wind power projects**: Eighteen projects with a total capacity of 926.76MW have been successfully executed. In November 2019, 12 power projects successfully attained financial closure.
3. **Bagasse energy:** Eight cogeneration projects utilizing bagasse as an energy source were successfully executed, resulting in a combined capacity of 259.1 MW.
4. **Wind power projects:** Solar power initiatives have been implemented, with a total installed capacity of 330 MW across five projects, while four projects with a capacity of 41.80 MW, were developed by Independent Power Producers (IPPs).
5. **Solar Hydro projects:** The utilization of small hydropower has contributed 128 MW, with an additional 877 MW currently in the implementation phase and 1500 MW available for future development.
6. **IFC** has launched a four-year initiative called Lighting Pakistan, aimed at promoting private investment to address the lighting requirements of buyers residing in remote areas of Pakistan.
7. **The National Action Plan for Sustainable Energy For All (**SE for All) in 2019 outlines strategies to achieve renewable energy targets assigned to AEDB, while the responsibility of achieving energy efficiency targets was assigned to NEECA. This plan aims to increase the proportion of renewable energy sources and enhance energy efficiency by a factor of two by the year 2030. The policy in Pakistan aims to address cooking fuel practices by implementing a strategy to provide alternative sources of cooking to approximately 14.03 million households by the year 2025.
8. **National Electric Vehicles:** The national policy about electric vehicles aims to achieve a 30% transition in the sales of electric vehicles for two and three-wheelers and heavy vehicles by 2030. This shift is anticipated to yield long-term advantages in improved urban air quality and reduced vehicular emissions from burning.

5.6.2 Adaptation Actions

Initiating a National Adaptation Plan (NAP) aligns with the short-term (2020-2025) objectives of the NDC 2016. The NAP aims to establish a structure that will facilitate integrating climate variations considerations into national policies and programs. This coordinated approach will involve multiple levels of implementation. The National Action Plan (NAP) aims to instill confidence in nature's restorative and regenerative capacity by allocating resources toward ecosystems as a strategy for mandatory adaptation.

5.6.2.1 Nature-based Solutions

i. **Ecosystem Restoration Initiative (2019-2030)** aims The Ecosystem Restoration Initiative (2019-2030) endeavors to integrate ecologically focused initiatives encompassing adaptation and mitigation measures. The endeavors encompass reforestation efforts, preservation of biodiversity, restoration of ecosystems, and formulation of policies. The Ecosystem Restoration Initiative (2019-2030) endeavors to integrate ecologically focused initiatives encompassing adaptation and mitigation measures. The endeavors encompass reforestation efforts, preservation of biodiversity, restoration of ecosystems, and formulation of policies.

ii. **Miyawaki Forests** have been established as pilot projects in various urban areas since 2019 to mitigate the urban heat island effect. One hundred twenty-six urban forest projects utilizing the Miyawaki technique are being executed nationwide.

iii. **The Recharge Pakistan** project, currently in the pipeline for 2019, seeks to employ floodwater to revitalize the wetland ecosystem and replace its aquifer. The proposed project has the potential to affect approximately 10 million individuals who are considered vulnerable. The anticipated outcomes include decreased flood hazards, heightened water safety, enhanced agricultural output and food security, community-based disaster risk management (CBDRM) implementation, and providing livelihood options resilient to climate change.

iv. **The Ten Billion Tree Tsunami Programme** is a major national initiative spanning four years (2019-2023) to expand the current forested regions. In the initial stage, 3.29 billion plants will be planted to rehabilitate nine distinct forest classifications across a land area of 1.2 million hectares by the year 2023.

v. **Transforming the Indus Basin** with Climate Resilient Agriculture and Water Management (2019-2026) involves a budget of US$ 47.7 million with the primary objective of enhancing the dissemination of information and employing advanced technology to augment the nation's ability to cope with climate-related issues in the agriculture and water domains.

5.6.2.2 Land Use Change and Forestry

i. **The Sustainable Land Management** (SLMP) 2015 to 2021 aimed to restore 10,000 acres of land, including 5,000 acres of plantations and 15,000 acres of receding land.

ii. **Sustainable Forest Management (SFM)** from 2016 to 2021 focuses on the regeneration and management of seven distinct forest landscapes, which collectively span an area of 145,300 hectares.

iii. **The National Forest Policy** of 2018 outlines the policies and guidelines for the management and conservation of forests in the country adopted a three-fold strategy: firstly, to preserve the currently forested areas; secondly, to enhance tree coverage by engaging the community; and thirdly, to fulfil international commitments about forests. Pakistan aims to augment its forest coverage from 5.4 per cent to 6.5 per cent by 2030.

iv. **The National Biodiversity Strategy and Action Plan (NBSAP)** 2018 outlines a comprehensive plan for the conservation and sustainable use of biodiversity within a nation. The objective is to preserve the biodiversity of forests and promote their sustainable utilization through the establishment of supportive institutional and policy frameworks, safeguarding and rehabilitation of forest ecosystem services, enhancement of native floral diversity, utilization of scientific research and contemporary technologies concerning forest biodiversity, and revision of the rights and concessions of local communities.

v. **They are restoring the mangrove forests project** aimed at the voluntary plantation, which drives the country to achieve an annual growth rate of 3.74% in its mangrove cover, positioning Pakistan as the only country in the region with a growing mangrove cover. Several public and private sectors and Civil Society Organizations (CSO) partnerships facilitated the planting of more than four million mangroves. According to the TBTTP, the province of Sindh has devised a plan to engage in a plantation initiative of 1.5 billion trees, primarily focusing on the mangrove regions.

vi. **The Sustainable Consumption and Production National Action Plan (SCPNAP)** outlines strategies for promoting sustainable consumption and production practices as outlined in SDG 12. These efforts have resulted in socioeconomic development, improved regional connectivity, and a healthier ecosystem.

5.6.2.3 Community Infrastructure

i. The primary objective of Glacial Lake Outburst Flood II is to offer timely indicators to vulnerable communities, enhance monitoring mechanisms, and implement 250 small-scale engineering interventions to alleviate the adverse effects of GLOF on the local populace's means of subsistence. This intervention is anticipated to bolster the resilience of communities vulnerable to the consequences of Glacial Lake Outburst Floods (GLOFs).

ii. The Snow Leopard and Ecosystem Protection Program (PSLEP) is a five-year endeavor from 2018 to 2023. The main goal of this initiative is to protect the snow leopard and its surrounding ecosystem in Pakistan.

iii. The Clean Green Pakistan Index has been formulated to improve municipal services. It employs a composite index comprising five fundamental pillars: water, sanitation, hygiene, solid waste management, and plantation. The primary objective of this initiative is to enhance urban cleanliness and hygiene by facilitating active involvement from local government entities and citizens. This entails prioritizing community engagement, evidence-based approaches, and the inclusion of local representation.

iv. Implementation of a Pilot Project to Prohibit Single-use Polythene Bags in Islamabad (2019-present): The objective of this initiative is to encourage source reduction and address the issue of plastic bag litter by enforcing a ban on single-use polythene bags within the city. Furthermore, proactive measures will be taken to involve and motivate residents to adopt reusable bags actively.

v. The primary objective of the Green Stimulus (2020) initiative is to address the economic repercussions of the COVID-19 pandemic by generating employment opportunities in environmentally sustainable sectors. Specifically, this initiative seeks to provide green jobs and livelihood options for individuals engaged in daily wage labour as part of the TBTTP program. The initiative encompassed the recruitment of 84,609 individuals to plant 430 million trees in 2020.

Chapter 6

CONCLUSIONS AND RECOMMENDATIONS

The lack of access to affordable, cleaner energy sources in Pakistan drives numerous households to continue using traditional biomass fuels such as firewood and dung cakes for their heating needs. This research examined Pakistan's household energy consumption patterns while assessing the emissions from traditional fuel use of firewood and dung cakes along with modern fuel types, including LPG and electricity..This research demonstrates that biomass fuels, particularly firewood and dung cakes, remain as dominant energy sources throughout rural Pakistan. Their use results from low cost and easy availability, coupled with a lack of modern clean energy technologies. These fuels are most commonly utilized by the less educated and very low-income households, meaning indoor emissions are worsened tremendously and pose severe health and environmental hazards. Without advancements in education, income, and infrastructure, cleaner energy solutions will do little to curtail reliance on biomass fuel. Addressing energy transition gaps requires a comprehensive strategy to alleviate just and sustainable energy transition challenges.

The present study highlights that biomass fuels, specifically firewood and dung cakes, remain widely used in rural areas of Pakistan. Biomass fuel use in cooking results in extensive production of hazardous substances that threaten household air quality. The disadvantages of traditional cooking practices demand superior technology, which reduces human health dangers along with environmental degradation. Dung cake emissions will continue to be high throughout all provinces unless effective control measures are established for traditional cooking fuel. Sustainable biomass management programs should run alongside public advocacy for alternative clean energy sources.

The low levels of LPG emissions require further measures to enhance LPG usage patterns to prolong its use, notably in rural areas where solid fuel dominates. Their utilization is attributed to easy availability, low cost, and limited access to modern clean energy sources. This reliance on biomass fuels is particularly common among low-income and less-educated households, significantly contributing to indoor emissions and posing serious health and environmental risks. The findings emphasize that reducing dependence on biomass fuels requires not only cleaner energy options but also improvements in education, income, and infrastructure. A comprehensive approach is essential to facilitate a just and sustainable energy transition.

In contrast, LPG and electricity, as modern fuels, are more prevalent among urban, educated, and higher-income households. The likelihood of adopting LPG as a cooking fuel is higher among female-headed and educated households, underlining the role of gender empowerment and awareness in clean energy transitions. However, regional disparities, especially in provinces like Sindh and KPK, highlight gaps in infrastructure and affordability. According to the present study, the province of Punjab needs to adopt energy-efficient measures and renewable energy technologies because it has the largest electricity emissions. Khyber Pakhtunkhwa (KPK) displayed the minimum electrical emissions.

The study investigated the household-level cooking emissions in Pakistan and examined their relationship with cooking expenditures. The results revealed a consistent upward trend, with emissions rising as expenditure increases. The results indicate that within the current socio-economic and structural framework, households do not transition towards cleaner cooking practices as their income increase. Instead, many households shift towards a combination of fuels, which may include both traditional and clean cooking fuels, resulting in sustained emissions.

The findings of the study suggest that higher education programs and awareness campaigns among women may help them acquire knowledge about the harmful effects of using biomass energy usage and the benefits of alternative energy sources such as LPG or solar and to gain skills related to sustainable energy practices, such as the use of clean and efficient stoves. Compared to traditional stoves, clean stoves are generally more efficient by reducing the amount of firewood burned and minimizing emissions by boosting their efficiency. By increasing household income and reducing family size, the government can further lessen the environmental impacts of firewood usage.

The research on household emissions in Pakistan has offered valuable insights into the environmental effects of various energy sources and consumption habits. The absence of an Environmental Kuznets Curve (EKC) pattern for cooking emissions and cooking costs indicates the urgent need for focused initiatives to promote cleaner cooking technology and practices.

The present study analyzed the factors contributing to household dietary emissions are a combination of demographic, regional and socioeconomic parameters. Households of educated female heads are related to an increase in emissions. As number of household members increases, and household head is daily wage worker dairy emissions are lower pointing to income dynamics determining consumption choices. In other words, emissions rise as household income levels increase , confirming that consumption levels are bad (for the planet). In the meantime, regional disparities are also important, as rural households emit less in some fruits and vegetables and more in dairy, while emissions also demonstrate very different patterns in various provinces such as Punjab and Sindh. These insights underscore the importance of targeted policies that take into account the local context and characteristics of households.

The following are the key results of the analysis, presented in concise summary form:

Carbon Footprints and Determinants: Consumer expenditure was identified as the primary driver of emissions. The hypothesis of the Energy Ladder is confirmed in this study, with a statistical decrease in the use of high-emission firewood (ß = -1.59) with rising expenditure, while an increasing demand for modern energy and other food exists.

Environmental Kuznets Curve (EKC): Statistical tests confirm an EKC relationship between emissions from cooking fuel and prosperity. The inverted U-shape is confirmed by a significantly positive linear expenditure coefficient (ß = +0.59) and a very significant negative squared expenditure coefficient (ß = -0.02), as shown in Table 4.14. This shows that, while prosperity raises emissions initially, it also leads to a fall afterward. However, policy interventions are required to hasten this transition.

Substitution Dynamics (Fuel & Food): Econometrically, it is revealed that households display fuel stacking rather than simple fuel switching, as evidenced by a high coefficient for the number of fuels used (ß = 2.760. The substitution effect between firewood and LPG is high; a rise in the LPG price is linked with a very high rise in the firewood budget share ß = 0.165 (Table 4.18). In the food sector, fruits and milk are classified as luxuries with elasticity greater than 1. Price measures were effective in shifting household demand towards lower-carbon staple foods (Table 4.22).

Mitigation Measures: Based on these dynamics, very specific mitigation measures are recommended. These include the imposition of price buffers to benefit from the high fuel substitution elasticity and the imposition of Carbon-Informed Food Pricing on luxury foods. The second is intended to contain the rise in indirect emissions that is fed by rising affluence.

6.1 Recommendations:

Based on the main analytical findings, the following policy recommendations and mitigation measures are suggested for managing domestic carbon emissions:

1. Accelerate the Transition to Clean Energy

Use Price Stabilization Mechanisms for New Fuels: The evidence supports a pervasive LPG-firewood substitution effect (ß= 0.165), where higher prices of LPG push households back into high-emission firewood. To counter this, government-intervened price buffers or targeted subsidies must be used to protect consumers, and particularly the poor and the middle class, from cleaner fuel price shocks. This allows a glide up the Energy Ladder without slippage.

Promote Appliance Stacking with Efficiency as a Goal: Because domestic "fuel stacking" is more prevalent than simple switching, policy would have to focus on rendering the stack cleaner instead. This can be achieved by subsidizing efficient biomass stoves for use in conjunction with LPG or electric cooktops. This is energy-secure as well as reducing the overall emissions of the household energy mix. Community based biogas plants: can be developed with the help of government subsidy.

2. Employ Economic Instruments for Consumption Choices

Apply Carbon-Informed Pricing to Luxury Foods: Since dairy and fruit are luxury foods with high elasticity of demand, their consumption will increase as one gets richer, which creates additional indirect emissions. A low, selective eco-tax can be applied to high-carbon luxury foods. The resultant tax revenue can be distributed to subsidize lower-emission staples and thus indirectly change the choice of consumer without punishing basic consumption.

Design Green Nudges and Information Campaigns: While price is an important driver, consumer knowledge can enhance policy effectiveness. Public information campaigns emphasizing the carbon cost of different foods and the health co-benefits of cleaner cooking fuels can facilitate households in changing over to more sustainable options.

3. Proactive Policy to "Flatten" the Environmental Kuznets Curve

Enact Targeted Interventions for Middle-Expenditure Families: Confirmation of the EKC for cooking fuels implies that emissions will eventually decline with growing prosperity. Policy intervention is required to lower the "peak" of this curve and accelerate the decline thereafter. Families on the cusp of upgrading to modern fuels must be intervened upon, economically and logistically supporting adoption of cleaner technologies before their emissions peak.

Investment in Clean Energy Infrastructure: The long-term strategy to irrevocably shift households away from biomass must be supported by robust infrastructure. This involves strengthening the electricity network to support electric cooking and increasing the LPG supply chain so that it is readily accessible in remote and rural areas, thereby breaking down adoption barriers.

6.2 Limitations of the study

This research provides unique insights into the causes of household-level direct and indirect emissions, despite significant challenges in research design and data collection. These limitations represent research opportunities. They are well-suited for conceptualizing future work in the area and for providing a balanced understanding of the current state of the work.

This research did not address the following design limitations.

1. Data Structure (Repeated Cross-Sections): Only data from the Integrated Household Survey for the years 2015/16 and 2018/19 were used. This case represents a repeated cross-section. Since the same households are not tracked, the analysis does not constitute a complete panel of data. Because of this, the analysis cannot understand the individual-level household dynamics (e.g., fuel-switching behavior) in the longer term.
2. Mitigate the effects of time-invariant household heterogeneity (e.g., culture-fixed preferences or unobserved infrastructure quality) that likely bias the long-term elasticity estimate in cases of household fuel transitions, dynamics, or switching.
3. Price and Endogeneity Estimates: Similar to other consumption-based household surveys, prices used in the demand functions are likely to cause endogeneity issues.

6.2.1 Directions for Future Research

The limitations of this thesis, along with the novel findings, naturally suggest several promising directions for future academic inquiry:

1. Dynamic Panel Data Analysis: The most critical future need is for an actual panel dataset of household consumption. With such data, researchers could employ dynamic panel data models (e.g., those incorporating lagged dependent variables) to identify better the influence of habit formation and state dependence in household energy consumption and fuel-switching behavior, moving beyond the current static analysis.
2. Integration of Behavioral Economics: Future models should incorporate variables that capture behavioral factors and constraints. Research could explore the influence of energy efficiency awareness, perceptions of fuel safety and convenience, and the role of social networks or peer effects on the adoption of modern, cleaner fuels like LPG and electricity, potentially using controlled field experiments or specialized survey modules.
3. Expansion of Consumption-Based Emissions Accounting: To provide a more complete picture, future studies should expand the scope of indirect emissions to encompass all major consumption categories. This involves integrating more comprehensive input-output models with household survey data to quantify the emissions embodied in housing-related energy (e.g., embodied carbon in building materials), transport, and durable goods.

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APPENDIX

Appendix Table A.1: Summary of Expected Signs based on economic theory and literature for Firewood Consumption and Emission Models (Heckman/Tobit)

Variable Name	Theoretical Rationale	Expected Sign on Firewood Accessibility (Heckman 1st Stage)	Expected Sign on Firewood Emission (Tobit)
Educated Females	Energy Ladder: Drives move away from traditional, high-emission fuels.	- (Negative)	- (Negative)
Dependent Family Members	Increased Need/Poverty: Increases total energy demand, often pushing use of accessible biomass.	+ (Positive)	+ (Positive)
LPG Price	Substitution: Higher price of a modern substitute increases demand for firewood.	+ (Positive)	+ (Positive)
Firewood Price	Own-Price: Law of Demand.	- (Negative)	- (Negative)
Household Expenditure	Energy Transition: Affluence enables switching away from traditional fuels.	- (Negative)	- (Negative)
Rural Location	Access/Availability: Easier access to biomass.	+ (Positive)	+ (Positive)
AC/Air Conditioner	Wealth Indicator: Though wealthy, the switch to cleaner fuel should reduce firewood use.	- (Negative)	- (Negative)

Appendix Table A.2: Summary of Expected Signs based on economic theory and literature for Dungcake Consumption and Emission Models (Heckman/Tobit)

Variable Name	Theoretical Rationale	Expected Sign on Dung Cake Accessibility (Heckman 1st Stage)	Expected Sign on Dung Cake Emission (Tobit)
Educated Females	Energy Ladder: Drives move away from all traditional biomass fuels.	- (Negative)	- (Negative)
Dependent Family Members	Increased Need/Poverty: Increases total energy demand; often a free resource.	+ (Positive)	+ (Positive)
LPG Price	Substitution: Higher price of modern fuel increases demand for this cheap alternative.	+ (Positive)	+ (Positive)
Dung Cake Price	Own-Price: Law of Demand (though often non-marketed, a high local price should reduce use).	- (Negative)	- (Negative)
Household Expenditure	Energy Transition: Affluence enables switching away from all subsistence fuels.	- (Negative)	- (Negative)
Rural Location	Access/Availability: Higher in rural areas due to livestock.	+ (Positive)	+ (Positive)

Appendix Table A.3: Summary of Expected Signs based on economic theory and literature for LPG Consumption and Emission Models (Heckman/Tobit)

Variable Name	Theoretical Rationale	Expected Sign on LPG Accessibility (Heckman 1st Stage)	Expected Sign on LPG Emission (Tobit)
Educated Female Head	Energy Ladder: Drives move toward modern, cleaner fuels.	+ (Positive)	+ (Positive)
Dependent Family Members	Budget Constraint: Large families are poorer and expected to rely on cheaper fuels.	- (Negative)	- (Negative)
Firewood Price	Substitution: Higher price of a traditional substitute increases demand for LPG.	+ (Positive)	+ (Positive)
LPG Price	Own-Price: Law of Demand.	- (Negative)	- (Negative)
Household Expenditure	Normal Good: Affluence increases capacity and demand for modern fuel.	+ (Positive)	+ (Positive)
Rural Location	Access Constraint: Less infrastructure/supply in rural areas.	- (Negative)	- (Negative)
AC/Air Conditioner	Wealth Indicator: Sign of high-income, though may compete for budget.	+ (Positive)	+ (Positive)

Appendix Table A.4: Expected Signs based on economic theory and literature for Fuel Share Models (AIDS Model)

These signs are for the effect on the budget share of each fuel.

Variable Name	Theoretical Rationale	Expected Sign on Firewood Share	Expected Sign on Dung Cake Share	Expected Sign on LPG Share
Own-Price	Law of Demand: Increased price reduces budget share.	- (Negative)	- (Negative)	- (Negative)
Cross-Price (LPG Price)	Substitution Effect: Shifts budget away from expensive LPG to traditional fuels.	+ (Positive)	± (Ambiguous)	N/A (Own-Price)
Cross-Price (Firewood Price)	Substitution Effect: Shifts budget away from expensive Firewood to LPG.	N/A (Own-Price)	± (Ambiguous)	+ (Positive)
Educated	Energy Ladder: Shifts consumption toward cleaner fuels.	- (Negative)	± (Ambiguous)	+ (Positive)
Rural	Access Constraint: Shifts consumption toward biomass.	+ (Positive)	± (Ambiguous)	- (Negative)