

Article

Nexus between Household Energy and Poverty in Poorly Documented Developing Economies—Perspectives from Pakistan

Iftikhar A. Shahid ^{1,2,*} , Kafait Ullah ¹ , Atif Naveed Khan ¹, Muhammad Imran Ahmed ³ , Muhammad Dawood ⁴, Clark A. Miller ² and Zafar A. Khan ^{5,6} 

- ¹ U.S. Pakistan Center for Advanced Studies in Energy (USPCAS-E), National University of Sciences & Technology (NUST), Islamabad 44000, Pakistan; kafaitullah@uspcae.nust.edu.pk (K.U.); 16phdatif@uspcae.nust.edu.pk (A.N.K.)
- ² School for the Future of Innovation in Society (SFIS), Arizona State University (ASU), Tempe, AZ, USA; clark.miller@asu.edu
- ³ School of Chemical & Materials Engineering (SCME), National University of Sciences and Technology (NUST), Islamabad 44000, Pakistan; imranrahbar@scme.nust.edu.pk
- ⁴ Klipsch School of Electrical and Computer Engineering, New Mexico State University (NMSU), Las Cruces, NM 88003, USA; dawood@nmsu.edu
- ⁵ Department of Electrical Engineering, Mirpur University of Science and Technology, Mirpur 10250, Pakistan; zafarakhan@ieee.org
- ⁶ School of Engineering and Applied Science, Aston University, Birmingham B4 7ET, UK
- * Correspondence: iftikhar.16phd@student.nust.edu.pk



Citation: Shahid, I.A.; Ullah, K.; Khan, A.N.; Ahmed, M.I.; Dawood, M.; Miller, C.A.; Khan, Z.A. Nexus between Household Energy and Poverty in Poorly Documented Developing Economies—Perspectives from Pakistan. *Sustainability* **2021**, *13*, 10894. <https://doi.org/10.3390/su131910894>

Academic Editor:
Alberto-Jesus Perea-Moreno

Received: 13 June 2021
Accepted: 23 September 2021
Published: 30 September 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Abstract: The indicators measuring socioeconomic wellbeing, such as the human development index (HDI) and multi-dimensional poverty indicator (MPI), recognize energy as an important resource for human development. However, energy did not find due weight in determining HDI or MPI, except as a fractional contributor to MPI calculations. This study presents a regression model to establish an energy–poverty nexus in Pakistan, utilizing a real-world dataset. Defining poverty in terms of per-capita income (PCI), the proposed model incorporates education-based parameters along with the energy-dependent indicators linked to households in Pakistan. The data aggregated at districts level are extracted from the Census 2017 campaign, Pakistan Bureau of Statistics (PBS). Statistical analyses indicate that energy-based identifiers correlate well with the PCI and augment the education-only model, capturing 94% variability in PCI vs. 78% for the education-only model. The study highlights the criticality of relevant data collection and data-driven planning in Pakistan for creating synergy in energy planning and poverty alleviation programs and provides recommendations for considering energy as an important and integral contributory factor in the human development index (HDI).

Keywords: sustainability; regression analysis; energy–poverty nexus; Pakistan; developing countries; human development index

1. Introduction

Energy, similar to food, clothing, and shelter, has long been an essential human need. As the world moved towards a more civilized living and increased mechanization, energy's role in attaining other human needs became apparent [1]. When energy-related developments started gaining momentum during the 20th century, access to and sustained availability of energy started impacting every facet of human life and development. In particular, last few decades saw increased interest of researchers in exploring energy's role in the societies' socioeconomic wellbeing [2–7]. In 1990, Alam et al. found a “significant” link between the physical quality of life and per-capita energy consumption using “World Energy Supplies” data, 1950–1974 [2]. During the year 2000, Alan D Pasternak, utilizing data from World Energy Supplies, 1997, delved into a quantitative relationship between

energy consumption and human wellbeing [3]. Volkan Ş. Ediger recommended the integration of energy as a component in calculating HDI in 2006, establishing a correlation between energy and HDI, which has education and income as two of the contributory factors in its calculation, through the statistical evaluation of HDR 2002–2003 [4]. By analyzing 1975–2005 human-development-related data from UNDP's database, Julia K. Steinberger and J. Timmons Roberts suggested in 2010 that a certain amount of energy must be provided for meeting human needs [5]. They used education and income as two of the related parameters in their study. Kalu Uduma and Tomasz Arciszewski attributed poverty in urban and rural Nigeria to poor energy supply in 2010 [6]. Again, in 2018, Christine W. Njiru and Sammy C. Letema established that there is a direct or indirect effect of energy on the living standards in society in Kenya using education and income as two of the studied elements [7]. Many contemporary experts agree that energy security can lead to the eradication of poverty, particularly in developing countries [8]. However, despite energy's dominant role in human development, the World Bank's "SE4All Global Tracking Framework" finds 840 million without electricity access and 2.0 billion people without clean cooking facilities as of 2017 [9]. This situation is not ameliorating over the years, in spite of a tremendous decline in the cost of renewable energy technologies between 2010 and 2017, the period during which the costs of solar energy and storage batteries reduced by 85% and of wind power generation by 49% [10].

Access to clean, reliable, and affordable energy has significant implications towards making a society affluent and sustainable, with direct as well as indirect effects on its long-lasting role towards poverty alleviation [1,6,8,11,12]. The indicators such as the human development index (HDI) and multi-dimensional poverty indicator (MPI) have been formulated and used for measuring socioeconomic wellbeing. Both indicators recognize energy as an important resource for human development, but energy did not find due weight in determining HDI or MPI, except as a fractional contributor to MPI calculations [13,14]. However, in 2015, energy did find recognition of its due importance through inclusion in seventeen Sustainable Development Goals (SDGs) adopted by the United Nations.

Available literature is replete with the evidence that energy impacts the earning capacity and, thus, income of a household through many enabling parameters such as learning opportunities, health, preventing loss of time, and better living conditions [2–8]. Access to modern energy services has been fully recognized as one of the critical resources for meeting daily life needs [15]. It has also been understood that dynamics and facets of the energy–poverty nexus vary across national economies and cultural contexts [6,7,16,17]. A growing body of research emphasizes that existing approaches for assessing energy poverty or access to affordable energy fail to fully account for the complex and dynamic interplay between energy insecurity and poverty [1,18]. Due to its social, economic, and environmental dimensions, harnessing the available renewable energy resources and their full utilization is now one of the most critical needs for any sustainable development and poverty alleviation program [1,15,19,20]. Additionally, the thriving living standards and growth rates of nations possessing, controlling, efficiently expending, and utilizing energy resources vs. abysmal living conditions and stunted growth rates of energy-deprived economies point towards a strong relationship between energy availability and its efficient utilization and overall wellbeing of the society [3,5]. It is, therefore, important to develop research contexts that characterize and explain the energy–poverty nexus within a specific sociocultural and economic context.

Similar to many developing countries, Pakistan is also heavily dependent on foreign energy resources for meeting its energy needs [17,21]. Dependence on the import of oil and gas to meet the energy needs alone has been the main contributor of trade imbalance for many decades, thus depleting foreign exchange reserves and raising foreign debt to an unsustainable level [17,22]. The allocation of a sizeable portion of national income for importing primary energy and for debt servicing has had adverse impacts on socioeconomic development in Pakistan [17,23]. This is another dimension of the energy–poverty nexus,

revealing how dependence on energy imports drains the resources of a poor country, resulting in the worsening of the overall state of poverty.

Despite the energy–poverty nexus being a reality, energy has not found its rightful place in studies and in poverty alleviation programs in developing countries including Pakistan. Numerous studies have already established the impact of household energy choices on education, health, quality of life, and wellness in society, indicating the interactive relationship between these parameters [3,15,24,25]. However, no research has quantitatively linked household energy type and wellness indicators such as per-capita income (PCI). Available literature is also limited in size and scope for linking the required amount and type of energy for raising the low-income population in Pakistan above the poverty line [17,21,23]. To the best of our knowledge, the energy–poverty nexus is not fully examined within the context of developing economies including Pakistan. Consequently, there has been no realization of the critical need for relevant data collection either. The availability of appropriate and reliable data could lead to synergized and sustainable poverty alleviation programs incorporating measures for the provision and productive use of energy [11,20]. Research on the impact of low-density, unclean, and unaffordable energy resources on the state of poverty is also limited [18,23,26,27]. Pakistan does not have any energy-linked poverty indicators based on which its energy policy can be aligned to contribute towards the reduction in poverty. The realization of the energy–poverty nexus within the context of developing economies in general, with particular reference to Pakistan, would help to align the poverty-reduction strategies and efforts.

It is well understood that education has a profound effect on alleviating poverty and improving earning abilities [24,25,28,29]. In this paper, in addition to education, we explore a statistical approach to establish the energy–poverty nexus through examining the close relationships between poverty levels, living standards, and types of household energy access and consumption at the district level across Pakistan. The energy–poverty nexus is established by examining and analyzing the household data collected through the yet-unpublished Census campaign in 2017 [30]. Our analyses provide an improved understanding of energy–poverty interplay, highlighting its oversized role in poverty/wellness, defined in terms of per-capita income (PCI). Further, this research attempts to provide a clear linkage between the PCI, and education, other economic indicators (i.e., living standard, etc.), and the type of household energy sources. This is likely to provide an insight to the policy makers to incorporate the household energy in the strategic planning for poverty alleviation programs.

To establish the energy-poverty nexus, we used linear regression analysis. Regression analyses are suitable for predicting continuous dependent variables, i.e., PCI, based on independent variables including education, living standards, and types of energy consumed. To this end, this paper is organized as follows: Section 2 explains the data, methods, and model used for the analysis. The results are presented in Section 3. Section 4 discusses the results, and the findings are summarized in Section 5, followed by study limitations in Section 6 and the conclusion in Section 7.

2. Data and Analytical Methods

2.1. Data Collection and Preparation

The socioeconomic wellbeing of a society is measured in terms of HDI, MPI, and/or PCI, among which HDI and MPI are better indicators. HDI, comprising three parameters, incorporates education and income. MPI has education, cooking fuel, sanitation, drinking water, electricity, and housing assets as six of its seven contributory elements. The district-level Census 2017 data for this research came from the Pakistan Bureau of Statistics (PBS). The data contain different parameters such as demography, literacy rate, education level, employment including that in foreign countries, homeless people, category, vintage and ownership status of housing, household facilities, the type of energy used for cooking and for lighting, household density, water, and access to media [30]. Unfortunately, HDI and MPI data covering the entire population of Pakistan is/was not available. On the other

hand, while PCI/income is not the optimum choice for measuring human development, it is often considered as the right indicator to evaluate poverty [7,15]. Available PCI data aggregated at the district level pertaining to federal capital and provincially administered districts (total 117 districts) were, therefore, obtained from the Pakistan Bureau of Statistics.

Thus, the explanatory variables for this study are based on selected parameters from both HDI and MPI besides the factors evaluated in earlier energy-wellness-related studies [2,7,15,20,23,24], whereas PCI, which depends on the earning ability and productivity of the household members, has been used as the outcome (dependent) variable. The PCI values are the average income per person per year for the respective district.

A sample size of 31 out of 117 districts was randomly selected to provide equal representation in all four provinces of Pakistan. The randomization ensured removal of any possible bias in our analysis, and the sample size of minimum 30 data points ensured t-distribution approaching the z-distribution [31]. All independent parameters pertaining to a given district were converted into percentages with respect to the population and number of households of that district.

The selected parameters, termed predictors, are grouped into five groups or categories, with 20 predictors in total:

1. Population parameters (PP)—literacy level, primary, secondary school certificate (SSC), degree (undergrad and above), and employed (working), (5 predictors).
2. Housing types (HT)—pakka (cemented houses), semi pakka (partly cemented), and kacha (not cemented/mud houses), (3 predictors).
3. Housing facilities (HF)—potable water, kitchen, bath, and toilet, (4 predictors).
4. Cooking energy fuels (CEF)—wood, gas, kerosene oil (K2 Oil), and others, (4 predictors).
5. Lighting energy sources (LES)—electricity, K2 Oil, gas lamps, and others (4 predictors).

2.2. Preliminary Data Analysis

As a preliminary step, the data matrix consisting of the above independent variables (or predictors) and the dependent variable, PCI, were subjected to correlation analysis. In that, the district-wide average or mean values of predictors showed a correlation (r) of 0.73 (p , 0.000) with the PCI. Additionally, strong positive and negative correlations were observed within various predictor variables. Literacy was correlated with primary and SSC ($r = 0.85$) and SSC with degree ($r = 0.78$). Cooking and lighting energy exhibited negative correlations: a very strong negative correlation ($r = -1$) between “gas” and “wood”, the two cooking fuel types, means the houses with gas supply do not need wood for cooking, and vice versa; a reasonable negative correlation ($r = -0.78$) between “electricity” and “K2 oil”, the two lighting sources, indicates that there is less likelihood that households with electric availability will need K2 oil for lighting; a correlation ($r = -0.94$) value between “pakka” and “kacha”-type houses implies that the two types are inversely interrelated. Additionally, all predictors are linear, ranging from 0% to 100%. This preliminary analysis indicated that a linear regression model may be suitable to provide a linkage between the predictors and the outcome, PCI, provided the following assumptions are met: (1) no predictors are perfectly correlated with each other (collinearity), (2) residuals have constant variance (homoscedasticity), (3) residuals are normally distributed, and (4) residuals are not correlated with each other (autocorrelation). We decided to explore the linear regression model via ordinary least squares (OLS) as well as Ridge regression. Since strong multicollinearity is indicated by the predictor variables, we decided to resolve this first as shown below. Ridge regression was discontinued after resolving the collinearity issues, as OLS provided adequate estimates. Detailed residuals analyses are presented in Section 3.

2.3. Data Analysis: Resolving the Collinearity Issue

In statistical analysis, two (or more) predictor variables are subjected to a multicollinearity test, since the phenomenon of multicollinearity leads to skewed results in

regression models [32,33]. Therefore, the selected parameters have been subjected to two-step analyses. The first step as explained below explores the existence of collinearity, resolves it by dropping the redundant independent variable(s), while retaining the remaining variables for regression analysis. During the second step, the retained variables are subjected to regression analysis.

The data matrix X consisting of 20 predictors (columns) and 31 districts (rows) are tested to establish a suitable predictive regression model. Since regression analyses are very sensitive to collinearity within the data matrix, the data matrix " X " is analyzed using Belsley [33] collinearity diagnostics function "collintest" in MATLAB[®] software. This test provides the "condition indices (CIs)" and the "variance-decomposition proportions (VDPs)" of the data matrix " X ". The CIs identify the number and strength of near dependencies in the data matrix " X ", whereas VDPs identify groups of predictors with interdependency coefficients between 0 and 1, and the extent to which the dependencies may degrade the regression. This test identified five interdependent groups with greater than 10 CIs (typical) and greater than 0.5 VDIs, namely, literacy and primary in PP, bath and toilet in HF, and all predictors within HT, CEF, and LES. In light of this test, 10 predictors x_1 through x_{10} (primary, SSC, degree, employed, pakka, potable water, kitchen, bath, wood, and electricity) were retained for subsequent analysis. These predictors were tested again for collinearity, and the resultant CIs and VDPs are shown in Figure 1 for each predictor variable. As can be observed in Figure 1, there is a mild collinearity between variables x_1 , x_2 , and x_{10} and variables x_6 and x_8 . However, these are very close to the VDPs tolerance of 0.5, indicating a marginal influence on regression, thus retained.

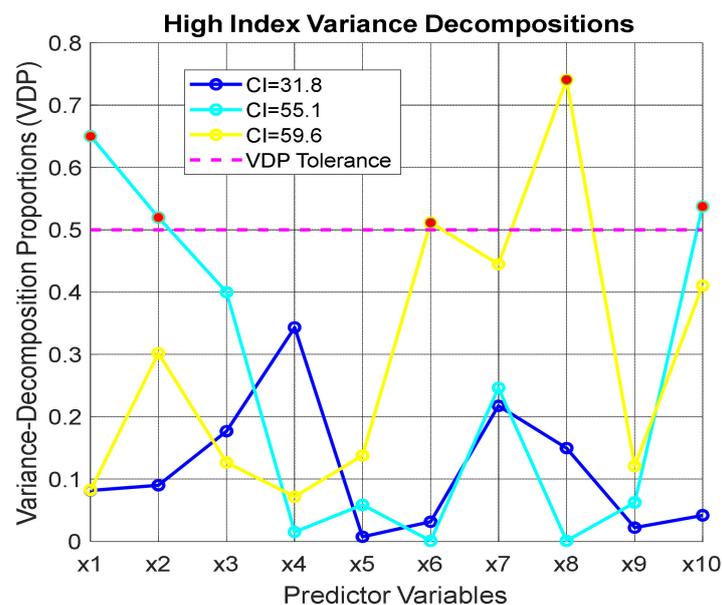


Figure 1. High-index variance decomposition of predictor variables, x_1 through x_{10} .

2.4. Data Analysis: Proposed Regression Model

The abovementioned 10 predictor variables along with the corresponding per-capita income (PCI), labelled as " y ", was tested for linear regression fit through the "stepwiselm" function of the MATLAB[®] with the p -value of F-statistics less than or equal to 0.05. This function creates a linear regression model using stepwise regression to add or remove predictors, starting from a constant model. At each step, the function searches for terms to add to the model or remove from the model, based on the p -value. This resulted in the following form of the regression model.

$$y \approx \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_5 x_5 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{39} x_3 x_9 + \beta_{910} x_9 x_{10} + \varepsilon \quad (1)$$

where β_0 is constant intercept, β_i for $i = 1, 2, \dots, 10$ are the coefficients or weights for each predictor variable, x_i . Further, there are two interaction or interdependent terms, x_3, x_9 and x_9, x_{10} , along with their respective coefficients, β_{39} and β_{910} .

The model in Equation (1) indicates that primary, SSC, degree in PP, pakka in HT, bath in HF, wood in CES, and electricity in LES might be the important predictors of per-capita income (PCI) in Pakistan.

3. Results

3.1. Model (1) Statistics and Its Fit to the Data

Table 1 provides pertinent statistics related to this model. ANOVA summary statistics are in Appendix A Table A1. As is evident from Table 1, model (1) accounts for roughly 94% variability in PCI, with the p -value being extremely small, indicating a robust fit and rejection of the null hypothesis. Similarly, the individual regression coefficients in model (1) have F-statistics-based p -values much less than 0.05, indicating a reasonably strong fit for each predictor. Further, regression models are used typically to provide interpolated predictions of y (in this case, PCI) for scenarios in which the data for predictor parameters are available. The proposed model (1) is likely to provide reasonable PCI estimates if the model variables, x_i , $i = 1, 2, 3, 5, 8, 9, 10$ are within the min/max limits in Table 1.

Table 1. Statistics pertaining to regression model (1).

Variables	Estimate	SE	tStat	DF	MeanSq	F	p -Value	Min	Max	Mean	SD
Intercept	−68.6156	224.2643	−0.3060				0.763				
x_1	11.4929	2.0395	5.6351	1	14,296	31.755	1.360×10^{-5}	7.94	30.83	16.94	5.11
x_2	−18.2715	3.4234	−5.3372	1	12,825	28.486	2.715×10^{-5}	5.27	20.31	10.22	3.49
x_3	−28.6171	9.5445	−2.9983	1	2599	5.7724	0.025608	1.43	8.56	3.10	1.52
x_5	2.0789	0.3603	5.7695	1	14,986	33.287	9.991×10^{-6}	2.37	85.38	49.29	24.09
x_8	1.3080	0.4936	2.6502	1	3162	7.0238	0.014969	58.74	98.46	84.15	11.78
x_9	4.4239	2.6253	1.6851	1	6275	13.939	0.0012267	9.26	97.94	70.32	21.98
x_{10}	5.9280	2.7878	2.1264	1	4429	9.8379	0.0049846	61.66	98.70	84.73	10.41
x_3x_9	1.1797	0.1908	6.1842	1	17,218	38.244	3.902×10^{-6}				
x_9x_{10}	−0.1127	0.0298	−3.7791	1	6430	14.281	0.0011005				
Error				21	450						
Number of observations (districts)		Error degrees of freedom	Root mean squared error		R-squared		Adjusted R-squared		F-statistics vs. constant model		Model p -value
31		21	21.2		0.957		0.939		52.1		2.36×10^{-12}

All predictors except x_9 , wood, individually are correlated positively with the PCI, as shown in Table 2 below. Therefore, PCI is likely to increase with an increase in all predictors except x_9 , wood.

Table 2. Predictors' independent correlation with the PCI.

Variables	x_1	x_2	x_3	x_5	x_8	x_9	x_{10}
Corr. Coef.	0.7921	0.6717	0.6128	0.7547	0.2311	−0.6158	0.8533
p -Value	0.0000	0.0000	0.0002	0.0000	0.2110	0.0002	0.0000

The differences between the magnitude and the signs of the coefficients in the regression model and the individual/independent correlation coefficients could be explained as follows: The regression model attempts to minimize the sum of the error squared between the regression-predicted PCI and the given PCI. The resulting weights (regression coefficients) and their respective signs (+/−) are assigned during this minimization process to estimate a linear line, as shown in Figure 2. As an example, x_2 (SSC) variable in Table 1 has a regression coefficient of (−18.2715), indicating that PCI will be depressed 18.2715 times for 1 unit increase in the SSC level of education of the underlying population. This inference is obviously not correct as the above correlation coefficient indicates for x_2 . The weights

and signs of regression coefficients are, therefore, adjusted to provide a regression model that minimizes the squares of the error.

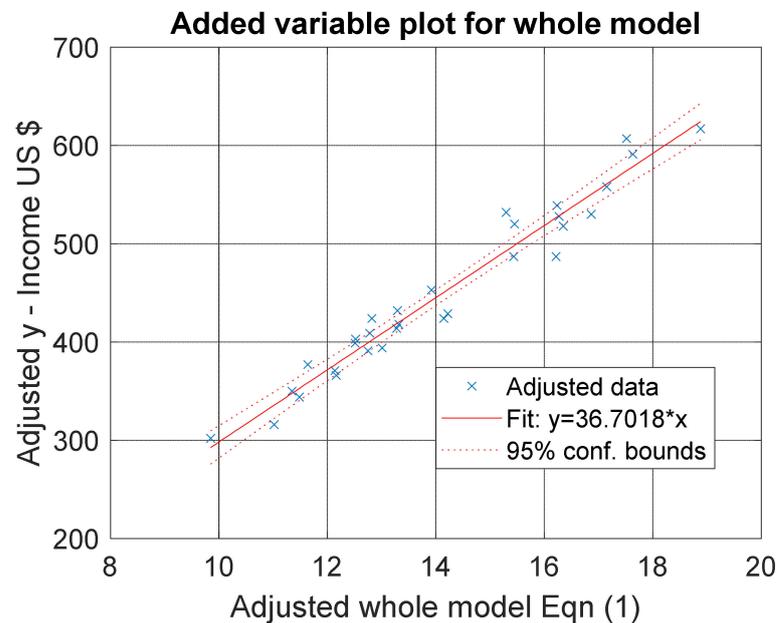


Figure 2. Regression model (1) vs. income in USD.

Figure 2 depicts the regression model (1) and its fit to the data. This figure also provides 95% confidence bounds, indicating that (1) is an appropriate model to represent PCI in Pakistan.

3.2. Interaction Terms in Model (1)

The model in Equation (1) has two interaction terms, x_3 and x_9 (degree and wood) and x_9 and x_{10} (wood and electricity). Both these interaction terms reinforce the validity of our hypothesis: there is a strong correlation between the type of energy available to and in use by the households and the income at the district level in Pakistan. Figure 3 shows the interaction between the percentages of degree holders and the users of wood. This suggests that PCI is depressed, as the use of wood increases until the degree holders' percentage is less than 5%. On the other hand, PCI is higher or likely to increase if the degree percentage is above 5% and the use of wood increases. This scenario points to the fact that while the increased use of wood indicates lowering the PCI of a household, more than 5% of members of the society with a higher education (degree) can compensate and improve the earning potential even in gas-deprived districts. Notwithstanding the impact of higher education, the interaction terms' relationship also indicates that increased use of poor-quality, low-density cooking fuel has depressing effects on PCI until another factor mitigates its impact.

As seen in Figure 4, there exists a strong negative correlation between x_9 and x_{10} (wood and electricity) beyond certain percentages of wood and electricity. Figure 4 indicates PCI increasing as the use of electricity increases provided the use of wood is less than 50%. Whereas, we see the PCI becoming depressed when the use of wood is beyond 50%, even if the electric connectivity is higher. This interactive relationship again confirms the dominant impact of poor-quality, low-density, and labor-intensive cooking fuel on the earning abilities of a household, even when they are provided with a better-quality and convenient lighting source. This phenomenon leads to the inference that it is necessary to improve the quality of energy for all the households' needs for eradicating poverty.

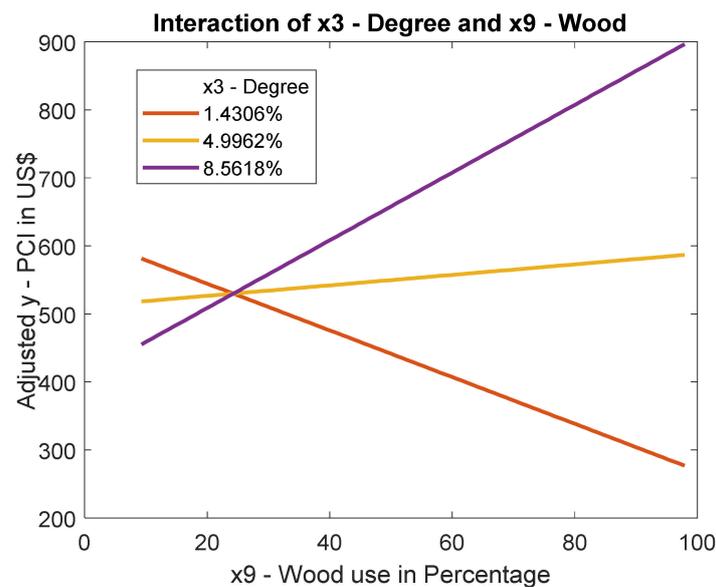


Figure 3. Interaction between degree and the use of wood in percentage.

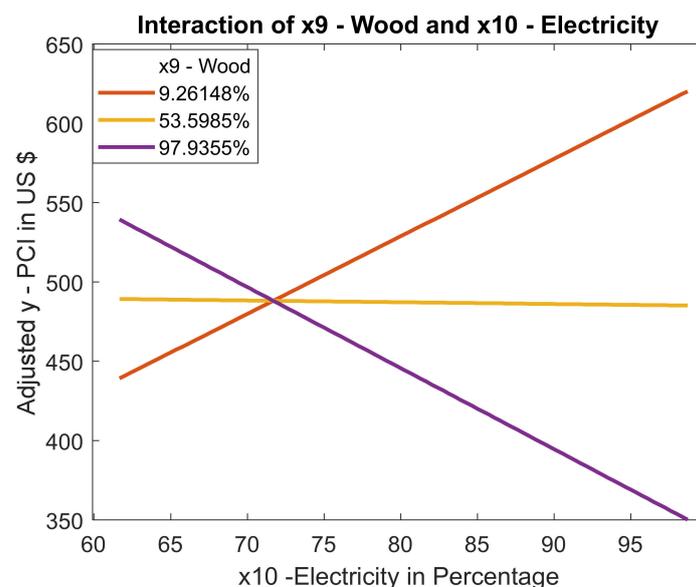


Figure 4. Interaction between the use of wood and electricity.

3.3. Residual Analysis of the Model (1)

Residuals, $(y - \hat{y})$, are helpful in detecting outlying PCI values and checking error term assumptions in the regression models. Three of the four assumptions (collinearity, normality, autocorrelation, and homoscedasticity) mentioned in Section 2.2 are analyzed in this section. Collinearity is already discussed under Section 2.2.

Normality: Shown in Figures 5 and 6 are two plots pertaining to the residuals of model (1) [33,34]. Figure 5 is Cook's distance vs. rows of observations, i.e., districts. Cook's distance is useful for identifying outliers in the data [33,34]. An observation with Cook's distance much larger than three times the mean Cook's distance is possibly an outlier. Figure 5 indicates that four districts fall slightly outside the range established by the Cook's distance. These four districts are, however, not considered as outliers when viewed in conjunction with the normal distribution plot in Figure 6. Figure 6 indicates that residuals are normally distributed, as assumed in the model; therefore, these four districts can be retained without violating normality assumptions.

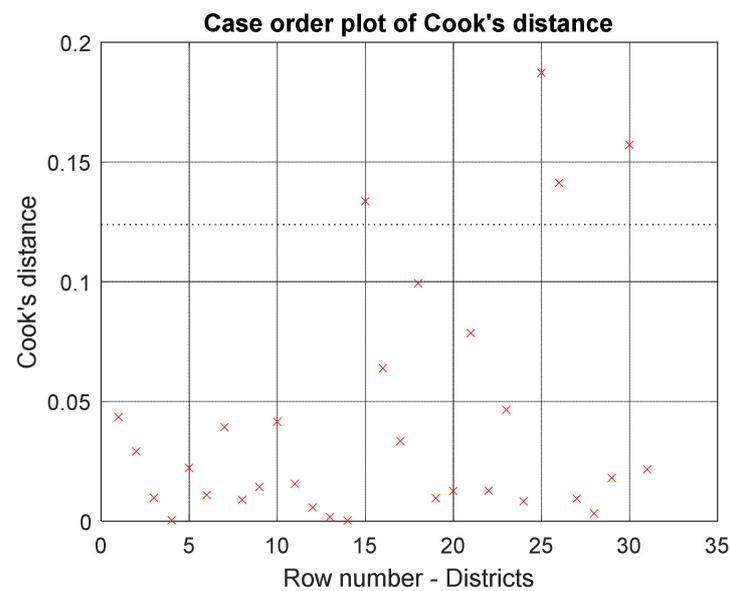


Figure 5. Cook's distance vs. observations, indicating 4 possible outliers.

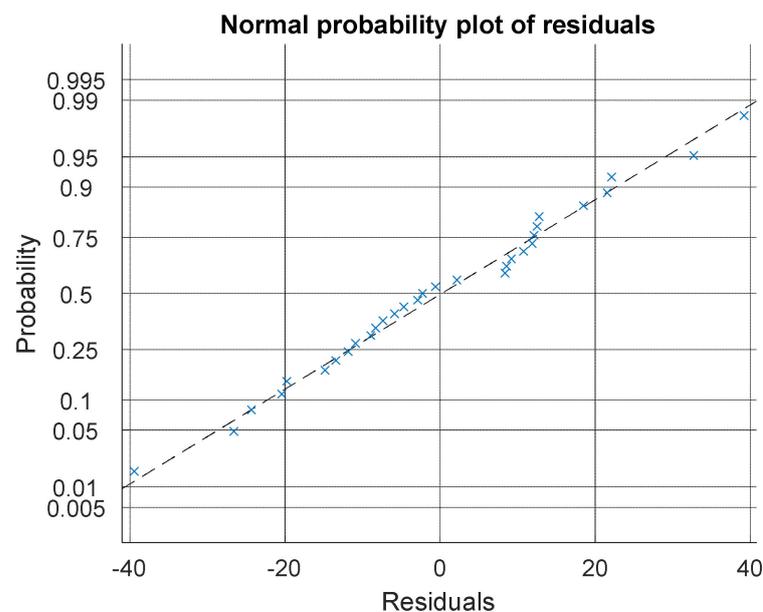


Figure 6. Normal probability plot of residuals, indicating approximate normal distribution.

Autocorrelation: Figure 7 shows the sample autocorrelation function or correlogram of raw residuals resulting from the difference between the fitted PCI and the observed PCI. The residuals are indicated within the 95% confidence bounds and are, thus, without significant serial correlation. This is further tested using Durbin–Watson (DW) [35] and Ljung–Box Q (LBQ) [36] tests for residual autocorrelation in MATLAB. Both tests assume no serial correlation as null hypothesis and return statistics upholding or rejecting this. DW statistics range from 0 to 4, with values between 1.5 and 2.5 indicating no significant serial correlation. For the data under consideration, DW statistics were 2.2 with a p -value of 0.78, indicating that no significant autocorrelation exists among the residuals. The LBQ test has the additional flexibility of testing at various lags. Since there exist some mild serial correlation at lags 2, 4, 5, 9, and 19, the LBQ test is used to identify this. The LBQ test returns either 0 (not rejecting null hypothesis) or 1 (rejecting null hypothesis) with a respective p -value at each location. The statistics for all lags were 0 with p -values ranging from 0.11 to 0.35, indicating that no serial autocorrelation exists among the data under consideration.

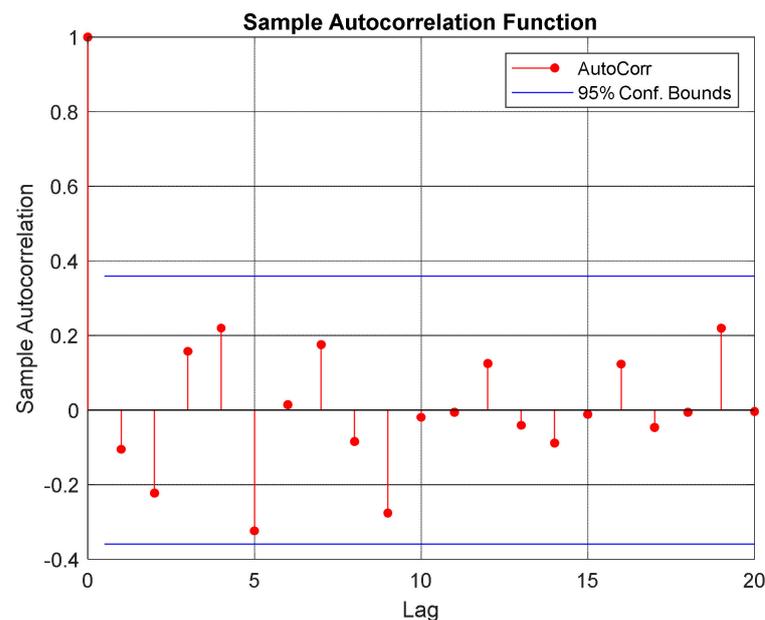


Figure 7. Sample autocorrelation function of residuals along with 95% confidence bounds. No significant serial correlation exists between the residuals.

Homoscedasticity: Homoscedasticity refers to all residuals having same variance. We used MATLAB's residual diagnostic function to test this. Shown in Figure 8 are residuals vs. fitted PCI. Although an obvious trend is not visible in Figure 8, we further tested the data to rule out possible heteroscedasticity. To this end, Breusch–Pagan (BP) [37] and Engle's autoregressive conditional heteroscedastic (ARCH) [38] tests were used. Both tests assume null hypothesis with no heteroscedasticity and return statistics upholding or rejecting this. The returned p -values of 0.6829 and 0.1023 for BP and ARCH, respectively, indicate upholding the null hypothesis so that there is no significant heteroscedasticity in the residual data.

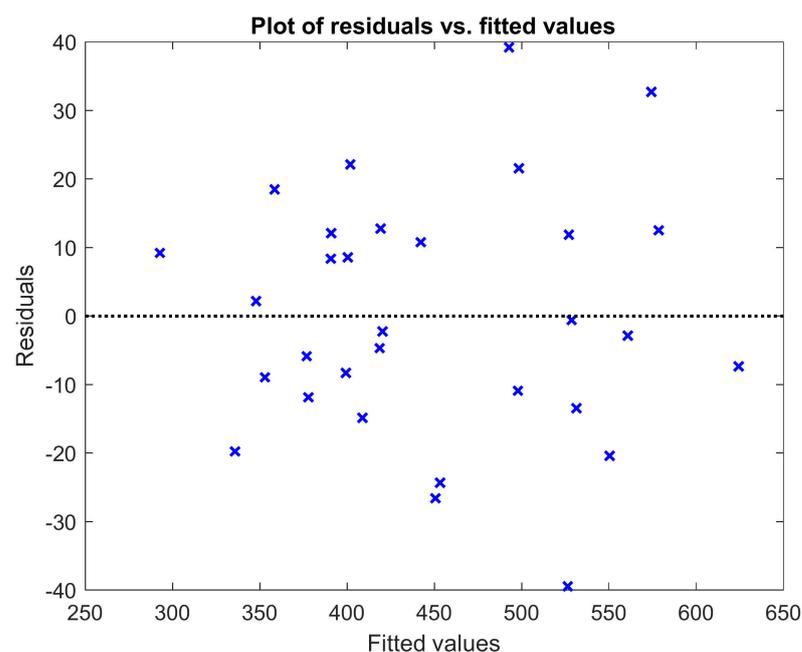


Figure 8. Residuals vs. fitted PCI, showing no significant heteroscedasticity.

Comparing residuals resulting from PLS and OLS: We compared residuals from PLS with those of OLS in Figure 9. The mean and standard deviation of the residuals,

respectively, for OLS and PLS are 0.00 and 17.75 and 0.00 and 29.93. Although we did not analyze PLS extensively, the residuals indicate an almost identical performance for both methods.

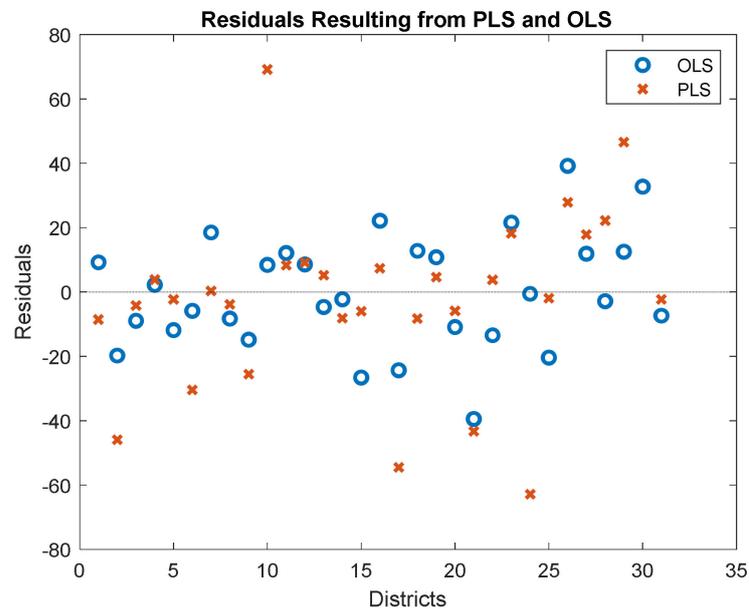


Figure 9. Residuals resulting from OLS and PLS, showing no significant difference.

Fitted or predicted OLS and PLS PCI for out-of-sample districts: The stepwise OLS model is generally considered not fitting the out-of-sample data adequately. To this end, 15 additional out-of-sample random districts are processed. Depicted in Figure 10 are fitted PCIs for these districts for OLS and PLS. The mean and standard deviation of the error resulting from fitted and observed PCIs (residuals), respectively, for OLS and PLS are 17.47 and 156.62 and 34.75 and 141.25. These results and the graphical representation in Figure 10 indicate an almost identical performance for both methods.

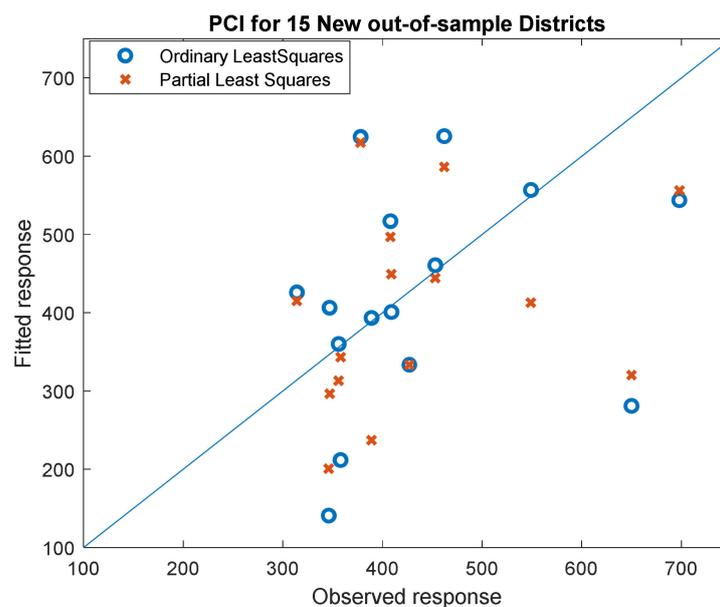


Figure 10. Comparison of fitted OLS and PLS PCIs for out-of-sample 15 districts. This shows no significant difference.

3.4. Comparison of the Proposed Model (1) with Education-Only Model

Several researchers have established the overarching impact of education on the individuals' earning abilities and the households' income [24,25,28,29]. In this section, a comparison is provided for the education-only model with that of the proposed model (1). For Census 2017 data, the education-only model accounts for 78% variability in PCI, as shown in Table 3. The mean regression plot pertaining to this model is shown in Figure 11. Comparing Figures 11 and 12 and Tables 1 and 3, model (1) captures 94% variability in PCI as compared to the education-only model with 78% coverage. Therefore, the proposed model (1) incorporating energy-related variables is more inclusive and better for estimating PCI for Pakistan. The proposed model augments the education-only model and, thus, establishes the relevance of household energy towards affluence/poverty in Pakistan. This model may be applicable in other developing economies too.

Table 3. Summary statistics pertaining to the education-levels-only model.

Variables	Estimate	SE	tStat	DF	MeanSq	F	p-Value	Min	Max	Mean	SD
Intercept	196.41	26.189	7.4999				4.5584×10^{-8}				
x_1	15.157	2.2327	6.7888	1	73,467	46.088	2.7254×10^{-7}	7.94	30.83	16.94	5.11
x_2	-12.108	4.8643	-2.4891	1	9876.1	6.1956	0.019266	5.27	20.31	10.22	3.49
x_3	38.765	8.4913	4.5653	1	33,223	20.842	9.7948×10^{-5}	1.43	8.56	3.10	1.52
Error				21	1594						
Number of observations (districts)	Error degrees of freedom		Root mean squared error		R-squared		Adjusted R-squared		F-statistics vs. constant model		Model p-value
31	27		39.9		0.805		0.783		37.2		1×10^{-9}

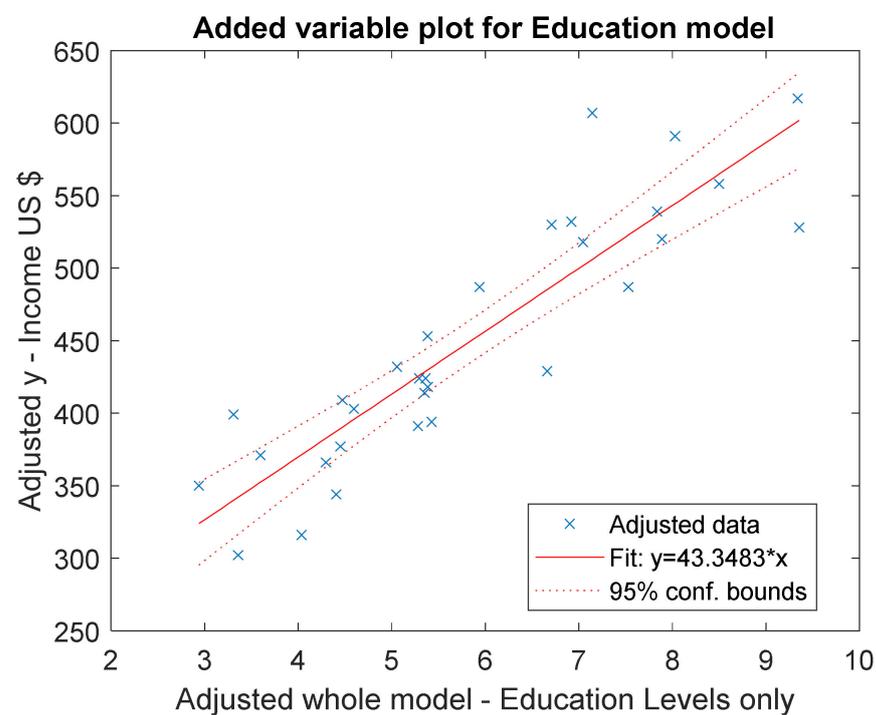


Figure 11. Education-only regression model vs. PCI in USD.

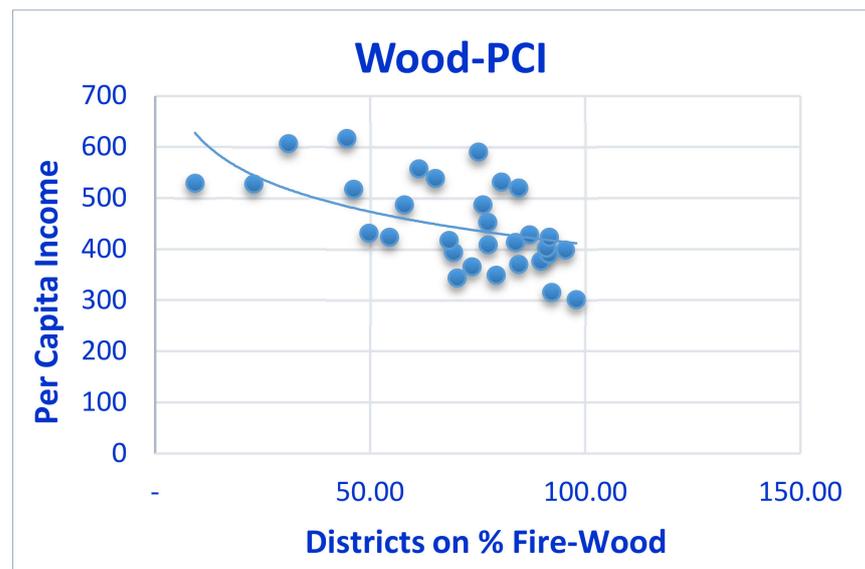


Figure 12. Negative impact of firewood on PCI at district level.

4. Findings

In light of Sections 2 and 3, we summarize the findings as follows:

- The data used in this research, though collected over extended time and by numerous individuals, are reliable, reflecting the real-life on-ground situation in Pakistan. Although this study has used a limited subset of this data, the analyses are likely to be applicable across the entirety of Pakistan except for a few highly developed urban centers or extremely remote rural areas.
- Education has an important linkage with the earning ability (PCI) of people in Pakistan, as is the case worldwide. The affluent population tends to aspire for greater schooling, high school, and college, and higher education enables for and offers better earning opportunities.
- Housing types and the facilities too are dependent on household income and are a good predictor of PCI.
- The critical energy–poverty nexus established through this work provides quantitative correlational evidence between energy and PCI at the district level in Pakistan. This correlation leads to the proposed model in Section 3, accounting for almost 94% variability in PCI.

5. Discussion

Notwithstanding the limitations mentioned in Section 6, the robust correlation between energy and one of the key indicators of social welfare, the per-capita income (PCI), opens venues for exploring some important dimensions of this relationship. Does this correlation fit into the existing predictors and indicators of wellness and poverty? Did energy find the right place in poverty alleviation programs in Pakistan? Should the energy type be included as an indicator in evaluating and reporting wellness/poverty/HDI and be incorporated in the development programs?

Historically, there exists a strong linkage of primary energy sources and the energy conversion industry with the state of affluence/poverty [3,5,11,20]. Based on the importance of energy in human development, energy found a central place in seventeen SDGs adopted by the UN in 2015 [39–41]. Energy access and poverty interdependence is well documented, and the importance of adequate energy had been identified earlier too: in the production of goods and supplies, in comfortable housing, for the provision of essential services such as health support and education, and even for the consumption of food [2,7,26,42–52].

During the last four decades, a few researchers concluded that energy-poor nations would experience a steep rise in human development relative to energy consumption [2,4]. In our study, we see a reasonably strong negative correlation of firewood with average PCI at the district level (Figure 12), pointing to the fact that increased use of poor-quality/inconvenient, low-density fuel contributes towards reduced income. Conversely, electric connectivity–PCI statistics indicate a positive correlation (Figure 13), meaning, thereby, that increased availability of clean and convenient energy would lead to better income. These findings closely mimic the energy–development relationship established through the earlier studies indicating the existence of the energy–poverty (affluence) nexus even at the district level in a developing country, specifically Pakistan. Thus, these graphs further validate the model arrived at through this research.

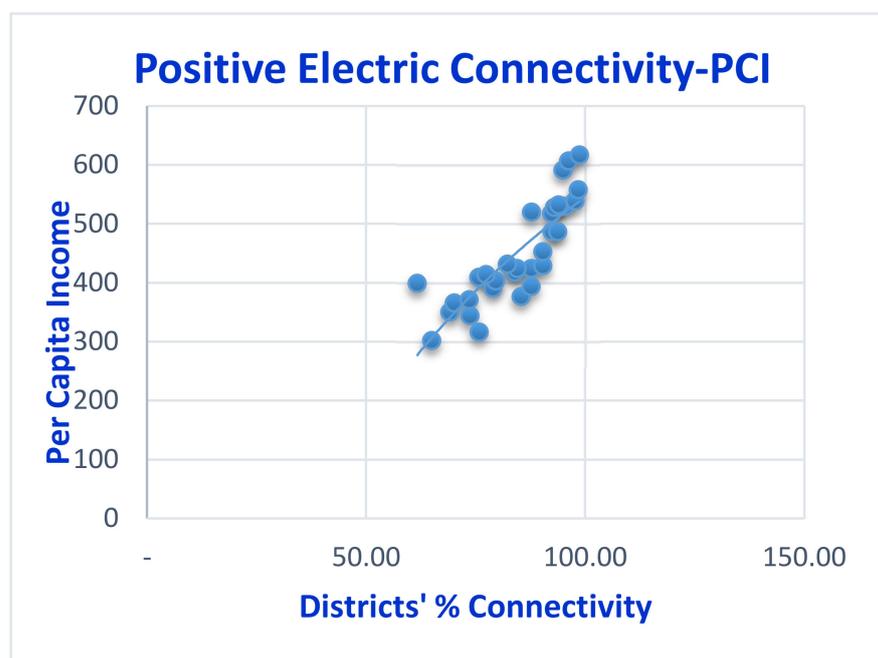


Figure 13. Positive electricity–PCI correlation at the district level.

The internationally accepted indicators of human development and state of wellness such as the human development index (HDI) and multi-dimensional poverty indicator (MPI) are mostly in use for measuring affluence and deprivation. Among these, HDI does not include energy as a component of human development [5], and household energy merely appears as a small fraction in MPI calculations [13,14]. The key statistic on the energy–poverty nexus brought forward through this work has shown a clear linkage of energy in measuring socioeconomic wellness in terms of PCI. Further, these statistical analyses corroborate some of the established and already in-use socioeconomic relationships such as the quality of dwelling and poverty, the households’ facilities and economic wellbeing, and the education levels and economic growth of the household [2,11,26,28,29,48,49].

Lack of adequate energy access has multi-faceted impacts on the social welfare of affected families in the form of poor health conditions, drained productive time, decreased chances of value addition through quality learning, diminished productivity, and limiting the wherewithal for income generation, thereby retarding overall development [17,45,51,53]. Similarly, continuous burning of wood for cooking has serious implications for the user, the society, and the world and is not at all sustainable [44,45,53]. In developing countries, mostly women and children are constrained to collect and bring the biofuels such as wood, straw, and animal dung in the energy-constrained households [43–45,49,52]. Such activities take the precious time of women and children, respectively, away from income-generating activities and schooling [43–45,54,55]. Lack of access to adequate energy resources is also partly responsible for child-labor practices in Pakistan [54]. Additionally, the lack of clean

energy sources is also the cause of the ill effects of indoor pollution, leading to 1.6 million yearly premature deaths, respiratory illnesses, eye diseases, and low-weight births [56,57]. Further, our planet, and particularly Pakistan, can ill afford the deforestation caused by firewood with serious environmental degradation and global warming impacts [23,43,44].

Millennium Development Goals (MDGs) adopted in the year 2000 were succeeded by Sustainable Development Goals (SDGs), which espoused seventeen goals and established interconnectivity between them [58]. Our statistical results and the ensuing discussion showed how most SDGs are directly correlated with SDG7, “Affordable and Clean Energy”. The attainment of SDG1, poverty eradication, is not possible unless everyone has access to “affordable” clean energy. The ill effects of unclean cooking fuels are a denial of SDG3, human health. The obligation to run for pollution-heavy biomass takes children away from the critical SDG4, quality education. The data presented above and related analysis indicate a strong electricity–education correlation of 72% (Table 4). Provision of clean water (SDG6) too has 48% dependence on electricity as per these data. The employment opportunities (SDG8) are also strongly correlated with electric connectivity (63%). Conversely, the unclean and inconvenient firewood that has adverse environmental impacts too (atmospheric degradation, deforestation, and increased carbon footprint) has a negative correlation with all these wellness parameters, highlighting the significance of affordable clean energy for other SDGs. Other SDGs were not covered during the Population Census 2017; however, SDG11—sustainable communities, SDG13—environmental protection, and SDG14/15—the life on earth are directly linked with the primary energy source types. Similarly, industrial/infrastructure development (SDG9) cannot be imagined without reliable and sufficient energy as its blood line. It is feared the SDGs will be far from achievement in 2030 if the developing economies do not realize and incorporate the provision of sustainable and affordable clean energy in their development plans.

Table 4. Impacts of clean and unclean energy on four SDGs.

Energy Source	Correlation Coefficient/Statistic			
	Education	Employment	Pakka Household	Water Accessibility
Electricity-Lighting	0.72	0.63	0.73	0.48
Wood-Cooking	−0.42	−0.23	−0.30	−0.25

The developed world and a few developing countries embraced the technological advancements and adopted policies for self-reliance in energy and for socioeconomic progress. In Pakistan, instead, the share of imported energy increased as reported by International Energy Agency, and it is no surprise that as of 2017, Pakistan’s HDI was the lowest in South Asia, after Yemen, Afghanistan, and Syria: three war-ravaged countries [52]. In per-capita energy consumption, Pakistan stood at 140th as per the latest available World Bank report [41]. Pakistan’s indicators on the productive use of energy as reported by the IEA are: Pakistan used 0.43 toe per 2005’s one thousand USD of GDP as against Bangladesh where 0.23 toe was consumed for the same outcome [59]. This elucidates the need for planning beyond energy supply and the importance of the productive use of energy in driving the economies towards poverty eradication.

Energy did appear as one of the nine pillars of development and poverty reduction in Pakistan’s agenda too during 2012, but it did not find any resources allocated for itself in the poverty-reduction plan [60]. On the energy side, focus has been on increasing energy supply and power generation similar to most developing countries [61]. Additionally, poverty alleviation programs never incorporated energy as a poverty-reduction goal either. In the 3rd quarter of 2019, Pakistan’s electric power generation surpassed the demand by many thousand megawatts, and the government was looking for “plans to utilize the surplus energy” [61]. Conversely, a repeated raise in electric tariffs is poised to reduce electricity demand further [62]. Unconsumed surplus power generation, continuously

rising circular debt, decreasing electricity demand owing to price escalation, heavy financial drain in subsidies, and heavily import-dependent power plants highlight the need for comprehensive outlook towards energy planning, its management, and governance in Pakistan. Not incorporating energy in poverty alleviation programs is likely to remain a major contributor to unachieved poverty alleviation and socioeconomic development goals.

Our findings validate the fact that households' fuel choices are dependent upon the socioeconomic conditions of the population [52,63,64]. This study does not assume a causal relationship between energy (and other explanatory variables) and the PCI except for the fact that life needs are met with physical and other resources, including energy. In line with the experts' opinion, there is also strong statistical evidence of the fact that the districts with more households using unclean and inconvenient source(s) of energy have much lower per-capita income [1,50,53]. Another critical dimension of energy usage is the outcome: whether it adds to the financial burden or is a resource for improving economic wellbeing [18,50,53]. The energy–income correlation shows a two-way interaction between energy and socioeconomic wellness, i.e., the energy is the means as well as the end [18,53]. Sustainable programs for poverty eradication and socioeconomic development through clean and affordable energy can be constituted based on relevant data only. The input data must cover all aspects of two-way interaction between energy and poverty so as to enable policy formulation and establishment of sustainable programs for poverty alleviation and development [63,64].

6. Limitations

Data-driven inferences are dependent critically on the processes of data collection and subsequently on the quality of the collected data. Additionally, no inference is valid unless mediated through local sociocultural environment. Based on the knowledge gained through the literature review and the sociocultural dynamics of Pakistan, certain limitations pertaining to available data used in this study are highlighted. The Census 2017 was a population survey and not an energy-related survey, although it captured predominant energy used in each household. The Census 2017, thus, provides, among other variables, information on the number of households using different type of energy for cooking and for lighting. However, information on the use of electricity for lighting is based on connectivity and does not cover reliability, quality, and affordability aspects of electrical energy. While according to the IEA's/IRENA's "The Energy Progress Report 2019" [41], Pakistan is the 4th largest unserved population, with another 144 million confronting reliability problems owing to frequent power outages. Data on the amount of energy consumed and the proportion of household income spent on energy are also not available. Households in Pakistan, similar to other developing countries, are constrained to use multiple sources of energy instead of relying on one, owing to inaccessibility to clean/high-density energy or unreliability of primary energy source [23,43,57]. Although the use of mixed fuels phenomenon remains unevaluated, the data used in this study cover the entire population of Pakistan, which may not be possible while conducting a customized survey. Thus, despite few limitations, the outcome of this study opens new avenues for taking a fresh look at the energy and its impacts on the poverty in Pakistan.

7. Conclusions

This study is a preliminary attempt to examine quantitatively the energy–poverty interplay in Pakistan with a possible extension to other developing countries. The study is unique, as it utilized detailed real data for Pakistan never used in any study thus far. The proposed regression model highlights the energy–PCI statistical correlation and energy's impact on aggregated household PCI. Since the study uses the final energy (wood and electricity) available to the households as two of the explanatory variables, it may be compared and contrasted with total energy input to the society in a country—a phenomenon used in earlier studies for exploring energy linkage with wellness. In addition to the education levels (a typical matrix linked to poverty) and other economic wellness

indicators, the proposed model highlights a close connection between energy and poverty, thereby augmenting the education-only model and suggesting it as one of the reliable factors to predict PCI. The model provides quantitative evidence on how a lack and/or availability of clean energy sources affects earning abilities and the income aggregated at the district level in Pakistan.

The critical energy-poverty nexus established through this work should help in better understanding the sustainability requirements and provide suitable guidelines for data collection and dissemination, as the availability of reliable data is critical in data-driven planning and implementation. This preliminary work may provide impetus to (1) the customized/focused data collection to fully explore the energy-poverty nexus in Pakistan; (2) creating synergy in energy planning and poverty alleviation programs, i.e., poverty mitigation through the adoption of clean and convenient renewable energy options; (3) drawing the researchers' and policy makers' attention to consider energy as an important contributory factor in human development and incorporate it as a parameter in calculating HDI; (4) invoke researchers' interest in further investigation into energy-poverty interplay in Pakistan and further studies comparing socioeconomic wellbeing between the communities with access to clean energy and those utilizing low-density unclean energy sources.

Author Contributions: Conceptualization, I.A.S. and C.A.M.; data curation, I.A.S. and M.D.; formal analysis, I.A.S. and M.D.; investigation, I.A.S.; methodology, I.A.S. and M.D.; project administration, I.A.S.; resources, I.A.S.; software, I.A.S. and M.D.; supervision, K.U., C.A.M. and Z.A.K.; validation, I.A.S., M.D. and C.A.M.; visualization, I.A.S.; writing—original draft, I.A.S.; writing—review and editing, K.U., A.N.K., M.I.A., M.D. and Z.A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The aggregated data for this research came from the Census 2017 campaign, Pakistan Bureau of Statistics. Although the data is not yet published fully, it is considered in public domain. No individual human subjects are identified in the census data. Therefore, IRB approval is not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data for conducting this research have been obtained from the Pakistan Bureau of Statistics. A summary of the compiled data is available on <https://www.pbs.gov.pk/content/population-census> (accessed on 10 April 2021). Detailed data have been released on special request, with restricted use instructions, and are held with the first/corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. ANOVA summary.

Variables	SumSq	DF	MeanSq	F	p-Value
Total	2.2074×10^5	30	7357.9		
Model	2.1128×10^5	9	23,476	52.144	2.3556×10^{-12}
Linear	1.9159×10^5	7	27,370	60.794	1.6186×10^{-12}
Nonlinear	19,693	2	9846.3	21.87	7.3441×10^{-6}
Residual	9454.4	21	450.21		

References

1. Energy Policy Guide: Harnessing the Power of Energy Access for Chronic Poverty Reduction—Chronic Poverty Advisory Network. Available online: <http://www.chronicpoverty.org/resources/2014/6/16/energy-policy-guide> (accessed on 10 August 2021).
2. Alam, M.S.; Bala, B.K.; Huq, A.M.Z.; Matin, M.A. A model for the quality of life as a function of electrical energy consumption. *Energy* **1991**, *16*, 739–745. [CrossRef]
3. Pasternak, D.A. *Global Energy Futures and Human Development: A Framework for Analysis*; US Department of Energy Report UCRL-ID-140773; Lawrence Livermore National Laboratory: Livermore, CA, USA, 2000.
4. JSTOR. Energy as an Indicator of Human Development: A Statistical Approach. Available online: <https://www.jstor.org/stable/24813002> (accessed on 10 August 2021).
5. Steinberger, J.K.; Roberts, J.T. From constraint to sufficiency: The decoupling of energy and carbon from human needs, 1975–2005. *Ecol. Econ.* **2010**, *70*, 425–433. [CrossRef]
6. Uduma, K.; Arciszewski, T. Sustainable Energy Development: The Key to a Stable Nigeria. *Sustainability* **2010**, *2*, 1558–1570. [CrossRef]
7. Njiru, C.W.; Letema, S.C. Energy Poverty and Its Implication on Standard of Living in Kirinyaga, Kenya. *J. Energy* **2018**, *2018*, 3196567. [CrossRef]
8. Tackling Energy Poverty. *One Earth* **2019**, *1*, 385–387. [CrossRef]
9. Progress Toward Sustainable Energy Global Tracking Framework 2015 Key Findings. Available online: https://stg-wedocs.unep.org/bitstream/handle/20.500.11822/7537/-Progress_Toward_Sustainable_Energy-2015Progress-Toward-Sustainable-Energy_2015.pdf.pdf?sequence=3 (accessed on 10 August 2021).
10. ThinkProgress. Renewables Are Winning the Economics Battle against New Coal and Gas, Stunning Study Shows. Available online: <https://thinkprogress.org/renewables-now-cheaper-than-new-coal-or-gas-across-two-thirds-of-the-world-c4980412cb53/> (accessed on 29 February 2020).
11. Bercu, A.-M.; Paraschiv, G.; Lupu, D. Investigating the Energy–Economic Growth–Governance Nexus: Evidence from Central and Eastern European Countries. *Sustainability* **2019**, *11*, 3355. [CrossRef]
12. Galvão, M.L.M.; dos Santos, M.A.; da Silva, N.F.; da Silva, V.P. Connections Between Wind Energy, Poverty and Social Sustainability in Brazil’s Semiarid. *Sustainability* **2020**, *12*, 864. [CrossRef]
13. OPHI. Global Multidimensional Poverty Index. Available online: <https://ophi.org.uk/multidimensional-poverty-index/> (accessed on 5 March 2020).
14. Human Development Reports. HDR Technical Notes. Available online: <http://hdr.undp.org/en/content/hdr-technical-notes> (accessed on 10 August 2021).
15. Masud, J.; Sharan, D.; Lohani, B.N. *Energy for All: Addressing the Energy, Environment, and Poverty Nexus in Asia*; Asian Development Bank: Mandaluyong, Philippines, 2007.
16. Geall, S.; Shen, W.; Gongbuzeren. Solar energy for poverty alleviation in China: State ambitions, bureaucratic interests, and local realities. *Energy Res. Soc. Sci.* **2018**, *41*, 238–248. [CrossRef]
17. Azam, A.; Rafiq, M.; Shafique, M.; Ateeq, M.; Yuan, J. Causality Relationship between Electricity Supply and Economic Growth: Evidence from Pakistan. *Energies* **2020**, *13*, 837. [CrossRef]
18. Ekholm, T.; Krey, V.; Pachauri, S.; Riahi, K. Determinants of household energy consumption in India. *Energy Policy* **2010**, *38*, 5696–5707. [CrossRef]
19. Miller, C.A.; Altamirano-Allende, C.; Johnson, N.; Agyemang, M. The social value of mid-scale energy in Africa: Redefining value and redesigning energy to reduce poverty. *Energy Res. Soc. Sci.* **2015**, *5*, 67–69. [CrossRef]
20. Casillas, C.E.; Kammen, D.M. The Energy-Poverty-Climate Nexus. *Science* **2010**, *330*, 1181–1182. [CrossRef] [PubMed]
21. Rehman, S.A.U.; Cai, Y.; Siyal, Z.A.; Mirjat, N.H.; Fazal, R.; Kashif, S.U.R. Cleaner and Sustainable Energy Production in Pakistan: Lessons Learnt from the Pak-TIMES Model. *Energies* **2019**, *13*, 108. [CrossRef]
22. Davis, D.H. *Energy Politics*, 4th ed.; St. Martin’s Press: New York, NY, USA, 1993.
23. Khyber, I.J.; Hayat, S. Determinants of Rural Household Energy Choices: An Example from Pakistan. *Pol. J. Environ. Stud.* **2012**, *21*, 635–641.
24. Tuyen, T.Q. Socio-Economic Determinants of Household Income among Ethnic Minorities in the North-West Mountains, Vietnam. *Croat. Econ. Surv.* **2015**, *17*, 139–159. [CrossRef]
25. Heckman, J.J.; Humphries, J.E.; Veramendi, G. Returns to Education: The Causal Effects of Education on Earnings, Health, and Smoking. *J. Polit. Econ.* **2018**, *126*, S197–S246. [CrossRef] [PubMed]
26. Kaygusuz, K. Energy for Sustainable Development: Key Issues and Challenges. *Energy Sources Part B Econ. Plan. Policy* **2007**, *2*, 73–83. [CrossRef]
27. Chakravarty, S.; Tavoni, M. Energy poverty alleviation and climate change mitigation: Is there a trade off? *Energy Econ.* **2013**, *40*, S67–S73. [CrossRef]
28. Baum, S.; Ma, J. *Education Pays: The Benefits of Higher Education for Individuals and Society*; Trends in Higher Education Series; The College Board: Mount Vernon, IL, USA, 2007.
29. Xu, H.; Hsu, W.-L.; Meen, T.-H.; Zhu, J.H. Can Higher Education, Economic Growth and Innovation Ability Improve Each Other? *Sustainability* **2020**, *12*, 2515. [CrossRef]

30. Pakistan Bureau of Statistics. Population Census. Available online: <https://www.pbs.gov.pk/content/population-census> (accessed on 10 August 2021).
31. Boslaugh, S. *Statistics in a Nutshell: A Desktop Quick Reference*; O'Reilly Media, Inc.: Sebastopol, CA, USA, 2012.
32. Snee, R.D. Regression Diagnostics: Identifying Influential Data and Sources of Collinearity. *J. Qual. Technol.* **1983**, *15*, 149–153. [[CrossRef](#)]
33. Cook, R.D. Influential Observations in Linear Regression. *J. Am. Stat. Assoc.* **1979**, *74*, 169–174. [[CrossRef](#)]
34. Cook, R.D. Detection of Influential Observation in Linear Regression. *Technometrics* **1977**, *19*, 15–18. [[CrossRef](#)]
35. Durbin-Watson Test with Residual Inputs—MATLAB Dwttest. Available online: <https://www.mathworks.com/help/stats/dwttest.html> (accessed on 13 August 2021).
36. Ljung-Box Q-Test for Residual Autocorrelation—MATLAB Lbqtest. Available online: https://www.mathworks.com/help/econ/lbqtest.html?s_tid=srchtitle_Ljung-Box%20Q-Test%20for%20Residual%20Autocorrelation_1 (accessed on 13 August 2021).
37. Heteroskedasticity Test—File Exchange—MATLAB Central. Available online: <https://www.mathworks.com/matlabcentral/fileexchange/24722-heteroskedasticity-test> (accessed on 13 August 2021).
38. Engle Test for Residual Heteroscedasticity—MATLAB Archtest. Available online: https://www.mathworks.com/help/econ/archtest.html?s_tid=srchtitle_Engle%20Test%20for%20Residual%20Heteroscedasticity_1 (accessed on 13 August 2021).
39. Sustainable Development Goals Fund. From MDGs to SDGs. Available online: <https://www.sdgfund.org/mdgs-sdgs> (accessed on 12 August 2021).
40. Schmidt-Traub, G.; Kroll, C.; Teksoz, K.; Durand-Delacre, D.; Sachs, J.D. National baselines for the Sustainable Development Goals assessed in the SDG Index and Dashboards. *Nat. Geosci.* **2017**, *10*, 547–555. [[CrossRef](#)]
41. Tracking SDG7: The Energy Progress Report (2019). Available online: </publications/2019/May/Tracking-SDG7-The-Energy-Progress-Report-2019> (accessed on 10 August 2021).
42. World Health Organization. *Situation Analysis of Household Energy Use and Indoor Air Pollution in Pakistan Department of Child and Adolescent Health and Development*; World Health Organization: Geneva, Switzerland, 2005.
43. Mishra, A. *Fuel for the Clean Energy Debate—A Study of Fuelwood Collection and Purchase in Rural India*; Policy Brief; South Asian Network for Development and Environmental Economics (SANDEE): Kathmandu, Nepal, 2008.
44. Kumar, S.K.; Hotchkiss, D. *Consequences of Deforestation for Women's Time Allocation, Agricultural Production, and Nutrition in Hill Areas of Nepal*; International Food Policy Research Institute: Washington, DC, USA, 1988; Available online: <https://books.google.com.pk/books> (accessed on 5 August 2021).
45. Karekezi, S.; Khennas, S.; Natu, S. Status of Biomass Energy in Developing Countries and Prospects for International Collaboration. In Proceedings of the 5th Global Forum on Sustainable Energy, Vienna, Austria, 11–13 May 2005.
46. Toman, M.T.; Jemelkova, B. Energy and Economic Development: An Assessment of the State of Knowledge. *Energy J.* **2003**, *24*, 93–112. [[CrossRef](#)]
47. Food and Agriculture Organization; World Energy Council. *The Challenge of Rural Energy Poverty in Developing Countries*; World Energy Council: London, UK, 1999.
48. Reddy, B.S.; Nathan, H.S.K. Energy in the development strategy of Indian households—The missing half. *Renew. Sustain. Energy Rev.* **2013**, *18*, 203–210. [[CrossRef](#)]
49. Cabraal, R.A.; Barnes, D.F.; Agarwal, S.G. Productive Uses of Energy for Rural Development. *Annu. Rev. Environ. Resour.* **2005**, *30*, 117–144. [[CrossRef](#)]
50. Doig, A.; Warwick, H. Smoke-The Killer in the Kitchen: Indoor Air Pollution in Developing Countries. 2004. Available online: <https://vtechworks.lib.vt.edu/handle/10919/67397> (accessed on 11 August 2021).
51. World Health Organization. *The World Health Report 2002: Reducing Risks, Promoting Healthy Life*; World Health Organization: Geneva, Switzerland, 2002.
52. Heltberg, R. *Household Fuel and Energy Use in Developing Countries—A Multicountry Study*; Oil and Gas Policy Division; The World Bank: Washington, DC, USA, 2003.
53. Hutton, G.; Rehfuess, E.; Tediosi, F.; Weiss, S. *Evaluation of the Costs and Benefits of Household Energy and Health Interventions at Global and Regional Levels*; World Health Organization: Geneva, Switzerland, 2006; ISBN 9241594799.
54. CNN. The 10 Worst Countries for Child Labor. Available online: <https://edition.cnn.com/2013/10/15/world/child-labor-index-2014/index.html> (accessed on 11 August 2021).
55. Rehfuess, E.; World Health Organization. *Household Energy and Health WHO Library Cataloguing-in-Publication Data*; World Health Organization: Geneva, Switzerland, 2006.
56. Akhtar, T.; Ullah, Z.; Khan, M.H.; Nazli, R. Chronic Bronchitis in Women Using Solid Biomass Fuel in Rural Peshawar, Pakistan. *Chest* **2007**, *132*, 1472–1475. [[CrossRef](#)] [[PubMed](#)]
57. Boy, E.; Bruce, N.; Delgado, H. Birth weight and exposure to kitchen wood smoke during pregnancy in rural Guatemala. *Environ. Health Perspect.* **2002**, *110*, 109–114. [[CrossRef](#)]
58. IEA Energy Atlas. Available online: <http://energyatlas.iea.org/#!/tellmap/-297203538> (accessed on 1 March 2020).
59. Data. Energy Use (Kg of Oil Equivalent per Capita). Available online: <https://data.worldbank.org/indicator/EG.USE.PCAP.KG.OE> (accessed on 1 March 2020).
60. Government of Pakistan. Ministry of Finance. Available online: https://www.finance.gov.pk/prsp_report_arc.html (accessed on 11 August 2021).

61. Active Circular Debt of Pakistan's Power Sector Hits Rs 860b. Available online: <https://tribune.com.pk/story/2075176/power-sectors-active-circular-debt-hits-rs860b> (accessed on 11 August 2021).
62. The Express Tribune. LSM Growth Contracts 6.5% in July–October. Available online: <https://tribune.com.pk/story/2120696/lsm-growth-contracts-6-5-july-october/> (accessed on 5 March 2020).
63. Miller, C.A.; Richter, J.; O'Leary, J. Socio-energy systems design: A policy framework for energy transitions. *Energy Res. Soc. Sci.* **2015**, *6*, 29–40. [CrossRef]
64. Understanding Poverty. Available online: <https://www.worldbank.org/en/understanding-poverty> (accessed on 11 August 2021).