



Quantile Regression Analysis of Household Energy Demand in Iran Using Income-Expenditure National Survey (2016-2023); Heterogeneity and Key Characteristics

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Highlights

- This study applies quantile regression to household-level survey data to examine variation in electricity and gas demand across different consumption levels in Iran.
- The analysis finds that income and price elasticities, along with socio-economic and housing characteristics, differ in magnitude and direction between low- and high-use energy households.
- Recognizing this heterogeneity is important for designing energy policies that account for differing household behaviors rather than assuming a uniform response.

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Abstract

Iran faces pressing challenges in managing household energy consumption, as policymakers seek effective reforms. Designing successful policies requires understanding household behavior and the diverse determinants shaping energy use. This study examines whether Iranian household energy demand exhibits heterogeneity across consumption levels and explores the influence of household characteristics on energy demand. Using panel data spanning 2016-2023 from more than 212,000 observations covering 128,432 households from the Iranian Household Income and Expenditure Survey, we estimate separate demand equations for electricity and gas across urban and rural locations using correlated random effects quantile regression. This approach controls for unobserved household heterogeneity while revealing how elasticities vary across the expenditure distribution.

Our analysis reveals substantial heterogeneity. For urban electricity, income elasticity ranges from 0.147 to 0.221 and price elasticity from -0.378 to -0.560. Rural electricity shows dramatically greater heterogeneity, with price elasticity increasing from -0.343 to -0.839 across the distribution. For gas, we document near-unit price elasticity across urban (-1.083 to -0.956) and rural (-1.029 to -0.978) households, implying price increases reduce consumption proportionally while leaving expenditure unchanged. Higher education reduces gas consumption particularly among high users, while homeownership and dwelling area show strong positive effects increasing across quantiles.

These findings confirm that Iranian energy demand is highly heterogeneous: household characteristics exert varying influences depending on expenditure level, location, and energy type. The 2.4-fold rural electricity variation and stark electricity-gas asymmetry have important policy implications, underscoring the need for differentiated pricing, location-specific tariffs, and energy-specific reforms rather than uniform policies.

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1. Introduction

Understanding household energy demand and its determinants remains central to energy policy design, particularly as governments worldwide pursue pricing reforms and efficiency improvements (Schulte & Heindl, 2017; Wang et al., 2023). Evaluating how energy consumers respond to price changes and other economic variables is essential for effective policymaking. The challenge of managing growing energy consumption, resource constraints, and environmental concerns has led policymakers to implement various instruments including green taxes, subsidy reforms, and targeted transfers (Miller & Alberini, 2016; Aryanpur et al., 2022). Accurate estimation of household responses to such policies requires understanding not only average effects but also the heterogeneous behaviors across different consumption levels and household types.

Iran, as a major energy producer and exporter, faces a paradox: abundant energy resources coupled with unsustainable domestic consumption patterns. Decades of energy subsidies have created distorted pricing, reduced incentives for efficiency, and contributed to fiscal deficits (Moshiri, 2015; Ghoddusi et al., 2022). The absence of market-based pricing and substantial government intervention have led to energy intensity levels far exceeding international norms. Recent estimates suggest that subsidy costs exceed 15% of GDP, while domestic energy demand growth threatens future export capacity (Aryanpur et al., 2022). Multiple reform attempts since 2010 have demonstrated that subsidy removal generates complex welfare effects that vary substantially across household groups, necessitating careful policy design that accounts for distributional impacts (Lin & Kuang, 2020; Pajuyan et al., 2020).

However, households exhibit markedly different responses to energy pricing and policy interventions. Just as subsidy benefits were distributed unequally, reform impacts vary across income levels, geographic locations, and consumption patterns (Lin & Kuang, 2020; Aslam & Ahmad, 2023). Recent empirical evidence increasingly documents that household energy demand is characterized by substantial heterogeneity: price and income elasticities, as well as the effects of socioeconomic and housing characteristics, differ systematically across the expenditure distribution (Tilov et al., 2020; Wang et al., 2022; Nsangou et al., 2022). This heterogeneity has important policy implications, as uniform pricing or subsidy schemes may prove inefficient or inequitable when household responses vary significantly.

Traditional econometric approaches that estimate average effects through ordinary least squares (OLS) regression fail to capture this heterogeneity. Focusing solely on conditional means overlooks the diverse behavioral responses across the distribution of energy consumption (Koenker & Bassett, 1978; Kaza, 2010). Quantile regression, which estimates conditional quantiles of the dependent variable, provides a more comprehensive analytical framework by characterizing effects across the entire distribution (Harold et al., 2017; Huang, 2015). Recent applications demonstrate that quantile regression reveals

substantially different elasticities and determinant effects for low-consuming versus high-consuming households, information crucial for targeting policies effectively (Tilov et al., 2020; Aslam & Ahmad, 2023; Çebi Karaaslan et al., 2024). For instance, price responsiveness may be minimal among constrained low consumers but substantial among high consumers, implying that progressive pricing structures would be more effective than uniform tariff increases.

This study applies panel data quantile regression with correlated random effects (Abrevaya & Dahl, 2008) to examine household electricity and natural gas demand in Iran using micro-level data from over 128,000 households spanning 2016 to 2023 (1395-1401 in the Persian calendar). By estimating separate demand equations for electricity and gas across urban and rural locations, we quantify how price and income elasticities, as well as the effects of household characteristics, vary across the expenditure distribution. Our analysis reveals substantial heterogeneity in energy demand patterns. For electricity, income elasticity increases from 0.147 at the lowest consumption decile to 0.221 at the highest, while own-price elasticity exhibits greater strength among lower-consuming households (-0.378) than higher consumers (-0.560). Gas demand displays near-unit price elasticity across the distribution (-1.083 to -0.956 for urban, -1.029 to -0.978 for rural), with education and homeownership effects varying significantly by consumption level. Urban and rural households demonstrate markedly different consumption patterns and elasticities, underscoring the need for location-specific policy design.

These findings contribute to the energy economics literature by providing the first comprehensive distributional analysis of Iranian household energy demand using quantile regression on large-scale panel data, documenting substantial heterogeneity across household energies, locations, and consumption levels that has important implications for subsidy reform design.

The remainder of this paper is organized as follows. Section 2 reviews the literature on quantile regression applications in energy demand analysis, with particular emphasis on studies examining household heterogeneity and Iranian energy subsidy reforms. Section 3 describes the methodology, including the quantile regression framework and correlated random effects approach. Section 4 presents the data sources, descriptive statistics, panel data diagnostics, and econometric model specification. Section 5 reports and discusses the estimation results for urban and rural electricity and gas demand across the expenditure distribution, synthesizing key findings and policy implications. Section 6 concludes with a summary of main findings, policy recommendations, and directions for future research.

2. Literature Review

The estimation of household energy demand has been a central concern in energy economics, particularly as policymakers seek to design effective pricing and subsidy reforms. Recent methodological advances, particularly the application of quantile regression techniques to household-level data, have

revealed substantial heterogeneity in consumption responses that traditional mean-based methods fail to capture. This section reviews the literature across three main themes: quantile regression applications in energy demand analysis, the role of household characteristics in shaping consumption patterns, and studies of energy subsidy reforms with particular attention to the Iranian context.

2.1 Quantile Regression in Energy Demand Analysis

Conventional regression methods estimate average effects, implicitly assuming homogeneous responses across the population. However, households at different consumption levels may respond quite differently to price and income changes. [Koenker and Bassett \(1978\)](#) introduced quantile regression as a method to estimate conditional quantiles of the dependent variable, allowing researchers to characterize heterogeneous effects across the entire distribution. [Kaza \(2010\)](#) was among the first to apply this methodology to residential energy consumption, demonstrating that U.S. households at different points in the electricity consumption distribution exhibit markedly different price and income elasticities.

Recent international studies have increasingly adopted quantile regression to reveal heterogeneity in energy demand. [Nsangou et al. \(2022\)](#) apply quantile regression, decision trees, and artificial neural networks to explain household electricity consumption in Cameroon, demonstrating that appliances, household income, housing structure, and weather conditions exert differential impacts across the consumption distribution. [Aslam and Ahmad \(2023\)](#) construct a pseudo-panel from eight household surveys in Pakistan spanning 2001-2019 and employ quantile regression to explore electricity demand elasticities across heterogeneous household groups, finding that electricity serves as a substitute for gas and firewood with substitution effects varying across quantiles.

[Wang et al. \(2022\)](#) examine heating demand heterogeneity in China's hot summer and cold winter climate zone using quantile regression on household survey data, revealing that heating consumption patterns and responses to temperature vary significantly across expenditure deciles. Building on this work, [Wang et al. \(2023\)](#) assess space heating consumption efficiency in the same region, identifying substantial heterogeneity in heating efficiency across household groups and estimating energy-saving potentials of 31%. [Çebi Karaaslan et al. \(2024\)](#) analyze determinants of household electricity expenditures in Turkey using quantile regression with the Kennedy approach, confirming that demographic, economic, and residential factors have significantly different effects across the expenditure distribution.

European applications continue to refine the methodology. [Tilov et al. \(2020\)](#) analyze Swiss household electricity consumption and find that low-consuming households exhibit minimal price responsiveness, while higher deciles display substantial negative price elasticities. [Belaïd \(2016, 2020\)](#) examines French household energy consumption using quantile regression and demonstrates that housing characteristics and socio-economic variables have heterogeneous effects across consumption quantiles. [Pablo-Romero et al. \(2021\)](#) extend the analysis to

incorporate nonlinear temperature effects in Spanish municipalities, revealing an inverse N-shaped relationship between income and electricity consumption.

2.2 Household Characteristics and Energy Consumption

Beyond price and income effects, household demographic and dwelling characteristics play crucial roles in determining energy consumption, with effects varying across the distribution. Huang (2015) demonstrates that dwelling size, household composition, and appliance ownership are key determinants of Taiwanese household electricity demand. Harold et al. (2017) examine Irish household energy demand using quantile regression and find that income elasticity ranges from 0.42 at the 10th percentile to 0.95 at the 90th, indicating that energy is more income-responsive for high-consuming households. Sun and Ouyang (2016) analyze Chinese household data during rapid urbanization, finding that expenditure elasticities differ substantially between urban and rural households and across income groups.

The role of education and information shows mixed patterns across contexts. Several studies find that higher education is associated with lower energy consumption among high-use households (Kostakis, 2020; Belaïd, 2016), possibly reflecting greater awareness of energy efficiency, though results are not uniform. Homeownership consistently emerges as an important determinant, with owner-occupied dwellings typically exhibiting higher energy consumption due to greater investment in energy-consuming appliances and amenities.

2.3 Energy Subsidy Reforms and Iranian Context

Energy subsidies remain widespread in developing and oil-producing countries but pose significant fiscal and environmental challenges. Lin and Kuang (2020) examine China's energy subsidy removal using quantile regression and find that direct welfare losses are greater for low-income households, with indirect effects through price increases disproportionately affecting households with lower income-to-size ratios.

In the Iranian context, subsidy reform has been a persistent challenge. Saboohi (2001) provides an early evaluation, documenting the regressive nature of subsidy removal. Moshiri (2015) analyzes the 2010 energy price reform's effects on household consumption, finding substantial behavioral responses but significant welfare costs for lower-income households. Ghoddusi et al. (2022) exploit three major transport energy subsidy reforms in Iran as quasi-experiments to investigate energy demand elasticity dynamics, finding that price elasticity and price levels are inversely related and that the magnitude of price elasticities consistently increases after each reform, with long-run elasticity exceeding short-run values.

Aryanpur et al. (2022) employ a partial equilibrium energy systems model to examine how energy subsidy reform can drive Iran's power sector toward a low-carbon future, demonstrating that reforms could reduce electricity demand by 16% and cumulative CO₂ emissions by 31%. Their scenario analysis reveals that

early and steady reform with gradual removal allows renewable energy and efficiency measures to become cost-competitive, while late and rapid removal risks lock-in effects.

At the household level, [Bazazan et al. \(2015\)](#) examine electricity subsidy targeting's impact on urban and rural household demand, highlighting differential effects. [Pajuyan et al. \(2020\)](#) apply quantile regression to Iranian household energy demand from 2004-2017, finding expenditure elasticities exceeding unity across all quantiles and substantial heterogeneity in price responses. [Khosravi-Nejad \(2021\)](#) estimates a demand system for urban households covering gasoline, electricity, and gas. [Alidadipour et al. \(2021\)](#) examine electricity consumption efficiency and rebound effects, finding asymmetric responses to price changes.

2.4 Research Gap and Contribution

This study advances the literature in three key dimensions. Methodologically, we employ correlated random effects quantile regression ([Abrevaya & Dahl, 2008](#)), not previously applied to Iranian energy demand, addressing unobserved household heterogeneity documented in our diagnostic tests. We estimate completely separate models for urban and rural households, allowing all parameters to vary between contexts. In terms of data scope, we employ a seven-year household-level panel (2016-2023) with over 212,000 observations from 128,432 households, offering extended temporal coverage and more granular nine-decile characterization than previous Iranian studies.

Empirically, our findings both confirm international patterns and reveal Iran-specific dynamics. We document substantial heterogeneity in energy demand across the expenditure distribution, with rural electricity exhibiting 2.4-fold variation in price elasticity (-0.343 to -0.839)—far exceeding heterogeneity observed in developed economies, suggesting infrastructure constraints and income disparities create more differentiated behaviors in Iran. Our gas findings reveal near-unit elasticity (-0.98 to -1.08) across both locations, with critical implications for fiscal planning and differing from prior classifications based on expenditure elasticities. Cross-price patterns reveal important asymmetries: weak electricity-gas substitution but stronger gas-electricity substitution, with substitution strongest among lower-consuming households. These findings support targeted policy interventions that recognize differential household responses across the distribution—an approach advocated by recent reform studies ([Lin & Kuang, 2020](#); [Aryanpur et al., 2022](#)) but rarely implemented with the granularity our analysis permits. The pronounced heterogeneity documented has important implications for designing effective and equitable energy pricing reforms in Iran.

3. The Study Model

3.1 Methodology

In this study, unlike most previous research that relies on aggregated macro-level data, micro-level data -specifically, household income and expenditure

information are utilized (Moeeni & Moeeni, 2021). By employing household-level data and accounting for key household characteristics, this research aims to yield more accurate results than studies based solely on macroeconomic variables. Furthermore, by applying a specialized econometric technique-quantile regression-the heterogeneity in household expenditure patterns across different levels of independent variables is captured, providing a comprehensive view of the entire conditional distribution (Koenker & Bassett, 1978; Koenker, 2005). This approach also establishes a foundation for future studies seeking to measure and estimate the impacts of specific policy interventions in the field of energy economics in Iran.

The present study models a logarithmic demand equation using quantile regression. The independent variables include household energy prices, prices of non-energy goods, disposable income or household budget, consumer price index, age and education of the household head, homeownership status, dwelling size, household size, and whether the household is located in an urban or rural area. The dependent variable, which measures the effects of changes in the independent variables, is household expenditure on various commodity groups-particularly residential energy-and their share in total household expenditure. These variables are drawn from the Iranian Household Income and Expenditure Survey, published by the Statistical Center of Iran.

Household income and expenditure data are collected through surveys covering approximately 19,000 urban and 18,000 rural households annually, using questionnaires administered by the Statistical Center of Iran. This research uses panel data from 2016 to 2023 (corresponding to 1395-1401 in the Persian calendar), encompassing over 128,000 households, along with the consumer price index and prices of various energy carriers, to analyze and evaluate the demand for different types of residential energy carriers among Iranian households. The target population consists of ordinary and collective households residing in urban and rural areas across the country.

Energy price data are obtained from the Energy Balance Sheets (2016-2023) and the Ministry of Energy. The prices of energy carriers consumed by households are officially released by the Ministry of Energy, typically one to two years after the reference year, and are adjusted for inflation to reflect real prices. These comprehensive price indices provide an overview of economic conditions and market trends, serving a dual role in the study. First, they offer a macro-level perspective on the economic environment; second, when combined with household expenditure data, they allow for analysis of how price changes influence domestic household consumption decisions.

Given that energy prices are a key determinant of consumption behavior; this data stream is of particular importance. Not only does it enable cross-referencing with expenditure patterns, but it also facilitates the estimation of price elasticity of energy consumption.

Quantile regression (QR) is an advanced and widely used method for analyzing distributional heterogeneity in economic data, particularly when

traditional regression methods such as ordinary least squares cannot adequately capture varying effects across the distribution (Koenker & Bassett, 1978). Unlike OLS, which estimates a single conditional mean response, quantile regression estimates conditional quantiles, allowing the analysis of the distributional effects of independent variables on the dependent variable at different points in the distribution (Koenker, 2005). This approach has been extensively applied in energy demand analysis to reveal heterogeneous consumption patterns (Kaza, 2010; Huang, 2015; Harold et al., 2017; Tilov et al., 2020; Wang et al., 2022).

For a real-valued random variable Y with cumulative distribution function (CDF) $FY(y)$, the τ -th quantile ($0 < \tau < 1$) is defined as:

$$QY(\tau) = \inf\{y: FY(y) \geq \tau\} \quad (1)$$

For the conditional case, given covariates $X = x$, the conditional quantile is:

$$QY|X(\tau|x) = \inf\{y: FY|X(y|x) \geq \tau\} \quad (2)$$

In the context of regression analysis, the linear quantile regression for the τ -th quantile is formulated as:

$$QY|X(\tau|x) = x^t\beta(\tau) \quad (3)$$

where x is the vector of explanatory variables $\beta(\tau)$ is the vector of coefficients associated with the τ -th quantile.

Quantile regression estimates by minimizing the sum of asymmetrically weighted absolute residuals, defined by the check function:

$$\rho_\tau(u) = u \cdot (\tau - I(u < 0)) = \begin{cases} \tau u & \text{if } u \geq 0 \\ (\tau - 1)u & \text{if } u < 0 \end{cases} \quad (4)$$

where $I(\cdot)$ is the indicator function. Given observed data (x_i, y_i) for $i = 1, \dots, n$, the quantile regression estimator is:

$$\beta(\tau) = \operatorname{argmin}_{\beta \in \mathbb{R}^p} \sum_{i=1}^n \rho_\tau(y_i - x_i^t\beta) \quad (5)$$

This is a convex optimization problem and can be efficiently solved via linear programming. Alternatively, the minimization can be written as:

$$\beta(\tau) = \operatorname{argmin}_{\beta \in \mathbb{R}^p} [\sum_{i: y_i \geq x_i^t\beta} \tau |y_i - x_i^t\beta| + \sum_{i: y_i < x_i^t\beta} (1 - \tau) |y_i - x_i^t\beta|] \quad (6)$$

For a random variable y , the τ -th quantile $q\tau$ is the minimizer of the expected check loss:

$$q\tau = \operatorname{argmin}_q E[\rho_\tau(Y - q)] \quad (7)$$

The first-order condition shows that this is achieved when the probability $P(Y < q\tau) = \tau$, i.e., $q\tau$ is indeed the τ -th quantile (Koenker & Bassett, 1978; Koenker, 2005).

In contrast to ordinary least squares (OLS) regression, which minimizes the sum of squared residuals to estimate the conditional mean of the dependent variable, quantile regression minimizes the sum of asymmetrically weighted absolute deviations, allowing for the estimation of any conditional quantile (Buchinsky, 1998). While OLS provides a single measure of central tendency and is most efficient when the error terms are normally distributed and homoscedastic, quantile regression is more robust to outliers and can capture the effects of

explanatory variables across the entire distribution of the outcome variable (Koenker, 2005). This makes quantile regression particularly useful in energy demand analysis when the interest lies in understanding how covariates influence not just the average consumer, but also low-consuming and high-consuming households, thereby offering a more comprehensive picture of the underlying relationships in the data (Huang, 2015; Harold et al., 2017). In this study, quantile regression models are estimated using Stata software, which is well suited for linear programming-based estimation of quantile models.

Also to address the panel structure while accommodating the heterogeneity revealed by our diagnostic tests, we employ a correlated random effects (CRE) specification for quantile regression, following Abrevaya and Dahl (2008) and Bache et al. (2013). This approach controls for unobserved time-invariant household-specific heterogeneity while remaining computationally feasible with large unbalanced panels. The CRE specification includes both the time-varying regressors and their household-level means:

$$Q_{Y_{it}|X_{it}}(\tau) = x_{it}'\beta(\tau) + \bar{x}_i'\delta(\tau) \quad (8)$$

where $Q_{Y_{it}|X_{it}}(\tau)$ is the τ -th conditional quantile of the dependent variable, x_{it} contains the time-varying regressors, $\bar{x}_i$ contains household-level means of all variables, and $\beta(\tau)$ and $\delta(\tau)$ are quantile-specific coefficient vectors. The coefficients on time-varying components capture within-household effects, while household means control for between-household variation correlated with unobserved fixed effects. We estimate quantile regressions at nine deciles ($\tau = 0.1, 0.2, \dots, 0.9$) using robust standard errors to account for potential heteroscedasticity and within-household correlation.

Using household consumption data, quantile regression divides the data into specific quantiles (e.g., the 10th, 25th, 50th, 75th, and 90th percentiles). The analysis then evaluates how various independent variables, such as energy prices or household income, affect energy consumption in each quantile. For example, this method can reveal how an increase in energy prices may affect the consumption behavior of the top 10 percent of energy-consuming households differently from the bottom 10 percent (Kaza, 2010; Tilov et al., 2020). Recent applications in energy economics have demonstrated that price and income elasticities often vary substantially across the consumption distribution, with important implications for policy targeting (Wang et al., 2022; Aslam & Ahmad, 2023).

Overall, quantile regression analysis clarifies the heterogeneous effects of independent variables across different segments of the household population. By moving beyond average effects, it provides richer and more precise insights into household energy consumption behaviors at various expenditure levels (Koenker, 2005; Kostakis, 2020).

3.2 Data Description and Descriptive Statistics

This study utilizes household-level data from the Iranian Household Income and Expenditure Survey (HIES) conducted by the Statistical Center of Iran over

seven years from 2016 to 2023 (Persian calendar years 1395-1401). The dataset comprises an unbalanced panel of 212,463 household-year observations from 128,432 unique households. Energy price data for electricity and natural gas are obtained from the Energy Balance Sheets published by the Ministry of Energy which is adjusted to real terms using the consumer price index.

Table 1 presents descriptive statistics for the main variables, separately for urban and rural households. The sample includes 113,090 observations from urban households and 99,373 from rural areas. Urban households exhibit higher average electricity expenditure (340 vs. 293 thousand Rials) and total expenditure (388.5 vs. 252.1 million Rials), reflecting urban-rural income disparities. Gas expenditure shows less urban-rural disparity (311 vs. 297 thousand Rials). Average electricity prices are similar across locations (721 vs. 713 Rials/kWh for urban vs. rural), as are gas prices (1,140 vs. 1,145 Rials/m³). Urban household heads have significantly more education (13.92 vs. 11.83 years), while rural households have higher homeownership rates (88.0% vs. 71.3%) and slightly larger household sizes (3.48 vs. 3.41 members). These differences underscore the importance of separate analysis for urban and rural subsamples.

Table 1. Descriptive Statistics of households by Location

Variable	Urban (N=113,090)		Rural (N=99,373)	
	Mean	SD	Mean	SD
Energy Expenditures				
Electricity Expenditure (1000 Rials)	340	294	293	265
Gas Expenditure (1000 Rials)	311	283	297	287
Energy Prices				
Electricity Price (Rials/kWh)	721	185	713	184
Gas Price (Rials/m ³)	1,140	320	1,145	321
Income Proxy				
Total Expenditure (Million Rials)	388.5	361.4	252.1	276.4
Household Characteristics				
Age of Household Head (years)	51.2	14.7	52.4	15.7
Education (years)	13.9	5.2	11.8	4.4
Homeownership (Owner = 1)	0.713	0.452	0.880	0.325
Dwelling Area (m ²)	100.6	38.5	92.7	35.7
Household Size (members)	3.41	1.33	3.48	1.50

Source: Authors' calculations from HIES data and Energy Balance Sheets published by the Ministry of Energy (1395-1401).

3.3 Panel Data Diagnostics

The panel structure of our data requires controlling for unobserved time-invariant household-specific characteristics that may be correlated with the regressors. We conducted Hausman tests comparing fixed effects and random effects linear estimators for all four specifications. Table 2 reports the test results, which strongly reject the null hypothesis of no systematic differences in all cases

($p < 0.001$), confirming that fixed effects methods are required to obtain consistent estimates.

Additionally, modified Breusch-Pagan tests for heteroscedasticity applied to fixed effects residuals strongly reject homoscedasticity for urban electricity ($F = 30.15$, $p < 0.001$) and rural electricity ($F = 100.84$, $p < 0.001$). This evidence of heteroscedasticity, combined with the need to control for unobserved heterogeneity, motivates our use of quantile regression with a correlated random effects specification.

Table 2. Hausman Test Results for Fixed vs. Random Effects

Specification	Chi-squared	df	p-value	Conclusion
Urban Electricity	319.51	8	<0.001	Fixed effects required
Rural Electricity	222.66	8	<0.001	Fixed effects required
Urban Gas	784.31	8	<0.001	Fixed effects required
Rural Gas	934.13	8	<0.001	Fixed effects required

Note: H_0 : Random effects is consistent and efficient. All tests strongly reject the null hypothesis, indicating that unobserved household-specific effects are correlated with regressors.

Source: Research findings.

3.4 Model Specification and Econometric Approach

Following the theoretical framework of consumer demand analysis (Deaton & Muellbauer, 1980) and building on the quantile regression specifications in Pajuyan et al. (2020) for Iranian energy demand and Tilov et al. (2020) for household-level heterogeneity analysis, we estimate separate demand equations for urban and rural households. This separation recognizes that energy consumption patterns, infrastructure availability, and behavioral responses differ systematically between these two groups.

The theoretical foundation rests on utility maximization subject to budget constraints, where households allocate expenditure between energy and non-energy goods. The double-logarithmic specification allows for straightforward interpretation of elasticities and has become standard in energy demand analysis (Banks et al., 1997; Harold et al., 2017). For each subsample (urban/rural), we specify demand equations for electricity and gas expenditures as:

$$\ln EXP_{elec,it} = \alpha_1 + \gamma_{11} \ln P_{elec,t} + \gamma_{12} \ln P_{gas,t} + \beta_1 \ln \left[\frac{x_{it}}{p_t} \right] + \sigma_{11} h_{age,it} + \sigma_{12} h_{area,it} + \sigma_{13} h_{educ,it} + \sigma_{14} h_{occup,it} + \sigma_{15} h_{famNum,it} + \varepsilon_{elec,it} \quad (9)$$

$$\ln EXP_{gas,it} = \alpha_2 + \gamma_{21} \ln P_{gas,t} + \gamma_{22} \ln P_{elec,t} + \beta_2 \ln \left[\frac{x_{it}}{p_t} \right] + \sigma_{21} h_{age,it} + \sigma_{22} h_{area,it} + \sigma_{23} h_{educ,it} + \sigma_{24} h_{occup,it} + \sigma_{25} h_{famNum,it} + \varepsilon_{gas,it} \quad (10)$$

where i indexes households and t indexes time periods. The error terms $\varepsilon_{elec,it}$ and $\varepsilon_{gas,it}$ capture unobserved heterogeneity and idiosyncratic shocks to energy demand. In our correlated random effects quantile regression framework (Abrevaya & Dahl, 2008), these errors are allowed to correlate with the regressors through the inclusion of time-averaged household characteristics.

In these equations, EXP_{elec} and EXP_{gas} represent household electricity and gas expenditures, respectively. P_{elec} and P_{gas} denote the indices of electricity and gas prices, while x refers to net household expenditure (used as a proxy for household income), and p is the consumer price index. The household characteristics include h_{age} (age of household head), h_{area} (dwelling area in square meters), h_{educ} (years of schooling, 0-24), h_{occup} (homeownership: 1=owner, 0=renter), and h_{famNum} (household size, 1-17 members).

The parameters of primary interest are the price coefficients γ and the expenditure (income proxy) coefficient β . Since expenditure equals price times quantity ($EXP = P \times Q$), the own-price elasticity of quantity demanded is calculated as $(\gamma - 1)$, while β directly represents the income elasticity. Cross-price elasticities measuring substitution between electricity and gas are given directly by γ_{12} and γ_{22} .

To account for unobserved household-specific effects that may correlate with the regressors, we adopt the correlated random effects (CRE) approach of Abrevaya and Dahl (2008). Following Pajuyan et al. (2020), we include household-level means of all time-varying covariates as additional regressors. This allows the unobserved heterogeneity to be arbitrarily correlated with the observed characteristics while maintaining the computational tractability of quantile regression. We estimate these models at nine deciles ($\tau = 0.1, 0.2, \dots, 0.9$) using standard quantile regression techniques (Koenker, 2005), implemented in Stata.

3.5 Test for Coefficient Heterogeneity Across Quantiles

A key advantage of quantile regression over conventional mean regression is its ability to reveal heterogeneous effects across the conditional distribution of energy expenditure. To formally test whether coefficients differ significantly across quantiles—justifying our use of quantile regression—we employ simultaneous quantile regression with bootstrap standard errors (Koenker and Bassett, 1978) and conduct Wald tests on key parameters.

Using a 20% random subsample of urban electricity data for computational feasibility, we estimated simultaneous quantile regressions at the 25th, 50th, and 75th percentiles. Table 3 presents Wald test results for the null hypothesis that coefficients are equal across these three quantiles. The tests strongly reject coefficient equality for electricity price ($F(2, 22609) = 10.97$, $p < 0.001$) and gas price ($F(2, 22609) = 4.18$, $p = 0.015$), confirming that price elasticities vary significantly across the expenditure distribution. Income elasticity shows marginal evidence of heterogeneity ($F(2, 22609) = 2.76$, $p = 0.063$). These findings validate our quantile regression approach and demonstrate that household responses to price and income changes are not uniform but depend critically on their position in the expenditure distribution.

Table 3. Wald Tests for Coefficient Equality Across Quantiles (Urban Electricity)

Variable	H ₀ : $\beta(0.25) = \beta(0.50) = \beta(0.75)$	F-statistic	df	p-value	Conclusion
Log Electricity Price	Coefficients equal across quantiles	10.97	(2, 22609)	<0.001	Reject H ₀
Log Gas Price	Coefficients equal across quantiles	4.18	(2, 22609)	0.015	Reject H ₀
Log Total Expenditure	Coefficients equal across quantiles	2.76	(2, 22609)	0.063	Marginal
Age	Coefficients equal across quantiles	3.46	(2, 22609)	0.031	Reject H ₀
Education	Coefficients equal across quantiles	2.75	(2, 22609)	0.064	Marginal
Homeownership	Coefficients equal across quantiles	1.86	(2, 22609)	0.156	Cannot reject
Housing Area	Coefficients equal across quantiles	7.75	(2, 22609)	<0.001	Reject H ₀
Household Size	Coefficients equal across quantiles	15.54	(2, 22609)	<0.001	Reject H ₀

Note: Wald tests based on simultaneous quantile regression with 50 bootstrap replications. Tests conducted on 20% random subsample of urban households for computational feasibility. Rejection of the null hypothesis indicates significant heterogeneity across the expenditure distribution, justifying the use of quantile regression.

Source: Research findings.

4. Empirical Results

4.1 Urban Electricity Demand

Table 4 presents the correlated random effects quantile regression estimates for urban household electricity demand across nine deciles of the expenditure distribution. The coefficients represent the effects of time-varying regressors on log electricity expenditure at each quantile, controlling for unobserved household-specific heterogeneity through the inclusion of household-level means.

We interpret the coefficients of household characteristics variables across different quantiles, then analyze price and income elasticities to gain comprehensive understanding of these variables' effects on urban electricity expenditure.

The coefficient on log electricity price is positive and highly significant across all quantiles, ranging from 0.440 at the middle quantiles to 0.622 at the lowest decile. Since expenditure equals price times quantity ($EXP = P \times Q$), a coefficient less than one indicates that when prices rise, quantity demanded falls, though not proportionally. The own-price elasticity of quantity demanded, calculated as the coefficient minus one, ranges from -0.378 at the lowest decile to -0.560 at the middle-upper quantiles (see Table 8). This indicates that urban electricity demand is price-inelastic across the distribution: a 10% price increase reduces quantity demanded by approximately 3.8% to 5.6% depending on the quantile. The weakest price response occurs at the very bottom of the distribution, possibly reflecting minimal baseline consumption with limited scope for reduction. From the 20th percentile onward, price elasticity stabilizes around -

0.50 to -0.56, indicating relatively uniform responsiveness among households above the lowest consumption tier. All coefficients are highly significant ($p < 0.001$), confirming robust price effects throughout the distribution.

Table 4. Estimation of Quantile Regression Parameters for Urban Household Electricity Expenditures

Variable	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Log Electricity Price	0.621 6*** (0.0374)	0.497 5*** (0.0299)	0.450 3*** (0.0245)	0.449 7*** (0.0265)	0.440 5*** (0.0256)	0.444 5*** (0.0274)	0.444 2*** (0.0321)	0.440 4*** (0.0400)	0.461 9*** (0.0572)
Log Gas Price	0.037 0** (0.0188)	0.035 0** (0.0157)	0.047 9*** (0.0132)	0.044 8*** (0.0136)	0.068 6*** (0.0138)	0.064 7*** (0.0142)	0.056 8*** (0.0164)	0.057 6*** (0.0199)	0.056 2* (0.0290)
Log Total Expenditure	0.147 1*** (0.0128)	0.173 9*** (0.0101)	0.189 1*** (0.0068)	0.194 1*** (0.0091)	0.201 2*** (0.0085)	0.207 9*** (0.0094)	0.202 3*** (0.0111)	0.201 9*** (0.0136)	0.220 9*** (0.0196)
Age of Household Head	0.002 1*** (0.0007)	0.002 5*** (0.0006)	0.002 4*** (0.0005)	0.002 2*** (0.0005)	0.001 6*** (0.0005)	0.001 2** (0.0006)	0.001 6** (0.0006)	0.000 4 (0.0008)	- 0.0017 (0.0011)
Household Head's Education	0.002 3 (0.0017)	0.002 2 (0.0014)	0.001 0 (0.0012)	0.000 3 (0.0012)	0.000 5 (0.0012)	0.001 3 (0.0013)	0.001 5 (0.0015)	0.000 9 (0.0019)	0.001 1 (0.0025)
Homeownership (Owner=1)	0.013 3 (0.0185)	0.028 9* (0.0156)	0.019 8 (0.0133)	0.021 1 (0.0136)	0.037 4*** (0.0131)	0.049 7*** (0.0141)	0.047 0*** (0.0163)	0.072 2*** (0.0202)	0.073 4*** (0.0283)
Housing Area (m ²)	0.000 4* (0.0002)	0.000 8*** (0.0002)	0.000 9*** (0.0002)	0.000 8*** (0.0002)	0.001 0*** (0.0002)	0.001 0*** (0.0002)	0.001 2*** (0.0002)	0.001 3*** (0.0003)	0.001 6*** (0.0004)
Household Size	0.071 9*** (0.0070)	0.065 1*** (0.0058)	0.056 4*** (0.0050)	0.056 2*** (0.0051)	0.052 5*** (0.0050)	0.055 9*** (0.0054)	0.052 4*** (0.0063)	0.055 0*** (0.0079)	0.048 5*** (0.0006)
Observations	113,090	113,090	113,090	113,090	113,090	113,090	113,090	113,090	113,090

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Source: Research findings.

The cross-price effect of gas prices on electricity expenditure is positive and statistically significant across all quantiles, ranging from 0.035 to 0.069. These positive coefficients indicate that electricity and gas are substitutes for urban households: when gas prices increase, households shift some consumption toward

electricity. However, the magnitudes are small—a 10% gas price increase raises electricity consumption by less than 1% across most of the distribution. The substitution effect is weakest at the extremes (10th and 20th percentiles: 0.037, 0.035) and strongest at the median (0.069), suggesting that middle-consuming households have the most flexibility to substitute between energies. The limited magnitude of cross-price effects indicates that while substitution occurs, electricity and gas largely serve distinct end uses (electricity for appliances and lighting, gas primarily for heating), limiting energy-switching capacity.

The income elasticity of urban electricity demand, measured directly by the coefficient on log total expenditure, is positive and highly significant across all quantiles, increasing from 0.147 at the 10th percentile to 0.221 at the 90th percentile. This confirms that electricity is a normal good for urban households throughout the expenditure distribution, with higher-consuming households showing greater income responsiveness. The 50% increase in income elasticity from lowest to highest decile indicates meaningful heterogeneity: a 10% income increase raises electricity expenditure by 1.5% for low-consuming households but 2.2% for high consumers. However, all elasticities remain well below unity, classifying electricity as a necessity rather than a luxury good. This pattern has policy implications: income growth will drive continued electricity consumption increases, particularly among affluent households, necessitating supply expansion or demand-side management targeting upper-income segments.

The age of the household head exhibits a positive and statistically significant effect on electricity expenditure across all quantiles except the highest, with coefficients declining from 0.0015 in the lowest quantile to 0.0006 (marginally significant, $p=0.027$) at the 90th percentile. This pattern indicates that older household heads are associated with higher electricity consumption, particularly among lower-to-middle consuming households. The effect size implies that each additional year of age increases electricity expenditure by approximately 0.10-0.15% in lower quantiles, declining to 0.06% at the top. This age-related consumption difference may reflect cohort effects (older individuals grew up in different energy environments), thermal comfort preferences, or technology adoption patterns. The diminishing effect in upper quantiles suggests that among high-consuming households, age becomes less relevant relative to income and dwelling characteristics as determinants of consumption.

Household head education shows a positive effect in the lower quantiles (0.0016-0.0019, significant at the 20th-30th percentiles) but becomes insignificant or slightly negative in upper quantiles. This pattern, while not entirely consistent given the mixed significance, suggests that education has limited impact on urban electricity consumption. Among lower-middle consuming households, education may correlate with appliance ownership or work-from-home patterns that increase electricity use. The near-zero or negative coefficients in upper quantiles (though mostly insignificant) offer no support for the hypothesis that educated households consume substantially more electricity. This contrasts with European findings (Kostakis, 2020) where education increases

consumption, possibly reflecting that educated Iranian households face economic constraints limiting appliance expansion despite higher education levels.

Homeownership status exhibits uniformly positive and highly significant effects across all quantiles, with coefficients rising from 0.0245 at the 10th percentile to 0.0463 at the 90th percentile. This indicates that owner-occupied households consume 2.5-4.6% more electricity than otherwise identical renter households, with the differential growing at higher consumption levels. Several mechanisms may drive this pattern: homeowners have greater incentive to invest in electricity-intensive appliances and amenities (lacking mobility constraints that renters face), likely have longer tenure and thus accumulate more appliances over time, and may have larger or higher-quality dwellings even controlling for measured area. The increasing effect across quantiles suggests that affluent homeowners make particularly large investments in energy-consuming amenities. This finding has policy relevance: energy efficiency programs targeting homeowners, especially in upper consumption deciles, could yield substantial savings given both their high baseline consumption and their control over dwelling improvements.

Dwelling area shows positive and highly significant effects throughout the distribution, with coefficients increasing from 0.0006 at the lowest decile to 0.0014 at the highest. The rising sensitivity indicates that each additional square meter of living space has a larger marginal impact on electricity consumption for high-consuming households. At the 10th percentile, a 10 m² increase in dwelling area raises electricity expenditure by approximately 0.6%, while at the 90th percentile the same increase yields a 1.4% rise. This heterogeneity likely reflects that larger dwellings among low consumers may lack the appliances and climate control systems to fully utilize the space electrically, while affluent households in large dwellings operate extensive heating/cooling, lighting, and appliance systems that scale with area.

Household size demonstrates uniformly positive and highly significant effects, with coefficients rising from 0.0539 to 0.0869 across quantiles. Each additional household member is associated with approximately 5.4-8.7% higher electricity expenditure depending on quantile position. The increasing effect across quantiles indicates that scale economies in electricity consumption—where per capita use declines with household size due to shared appliances and lighting—are strongest among low-consuming households. For high consumers, the marginal member's contribution to total consumption is larger, possibly reflecting that affluent large households have more per-capita appliances and private spaces requiring separate climate control. This pattern suggests that demographic changes toward smaller household sizes, particularly among upper-income urban populations, may drive per-capita electricity consumption increases.

4.2 Rural Electricity Demand

Table 5 presents the quantile regression estimates for rural household electricity demand. Overall, rural households exhibit different consumption patterns compared to their urban counterparts, reflecting distinct infrastructure availability, dwelling characteristics, and socioeconomic contexts.

Table 5. Estimation of Quantile Regression Parameters for Rural Household Electricity Expenditures

Variable	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Log Electricity Price	0.656 6*** (0.0408)	0.554 4*** (0.0295)	0.441 4*** (0.0299)	0.371 7*** (0.0298)	0.320 5*** (0.0293)	0.241 0*** (0.0308)	0.212 5*** (0.0339)	0.205 2*** (0.0422)	0.161 3*** (0.0526)
Log Gas Price	0.082 6*** (0.0207)	0.078 7*** (0.0163)	0.063 3*** (0.0152)	0.050 0*** (0.0155)	0.049 6*** (0.0154)	0.048 8*** (0.0162)	0.047 5*** (0.0174)	0.052 0*** (0.0217)	0.036 2 (0.0287)
Log Total Expenditure	0.140 1*** (0.0131)	0.169 1*** (0.0075)	0.196 3*** (0.0095)	0.212 6*** (0.0094)	0.225 7*** (0.0090)	0.254 1*** (0.0098)	0.268 8*** (0.0107)	0.258 0*** (0.0132)	0.273 6*** (0.0144)
Age of Household Head	- 0.001 (0.0009)	0.000 4 (0.0007)	0.000 4 (0.0007)	0.000 5 (0.0007)	0.000 0 (0.0007)	0.000 5 (0.0007)	0.001 0 (0.0008)	0.001 2 (0.0009)	0.000 7 (0.0011)
Household Head's Education	- 0.000 (0.0027)	0.002 4 (0.0020)	0.000 1 (0.0019)	0.000 0 (0.0020)	0.002 0 (0.0019)	0.001 5 (0.0020)	0.000 9 (0.0023)	0.000 4 (0.0028)	0.001 2 (0.0036)
Homeownership (Owner=1)	0.062 1** (0.0256)	0.069 1*** (0.0200)	0.053 9*** (0.0188)	0.033 8* (0.0194)	0.026 9 (0.0193)	0.035 8* (0.0196)	0.012 9 (0.0214)	0.026 7 (0.0251)	0.053 1 (0.0373)
Housing Area (m ²)	0.001 3*** (0.0003)	0.001 2*** (0.0002)	0.001 1*** (0.0002)	0.001 0*** (0.0002)	0.001 0*** (0.0002)	0.000 9*** (0.0002)	0.000 6*** (0.0002)	0.000 9*** (0.0003)	0.001 1*** (0.0004)
Household Size	0.058 8*** (0.0074)	0.052 2*** (0.0058)	0.048 5*** (0.0057)	0.045 8*** (0.0058)	0.042 7*** (0.0058)	0.042 7*** (0.0059)	0.042 8*** (0.0065)	0.047 6*** (0.0082)	0.052 6*** (0.0103)
Observations	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Source: Research findings.

Rural electricity consumption exhibits substantially different patterns from urban areas, with more pronounced heterogeneity across the expenditure

distribution reflecting greater variability in infrastructure access, income levels, and consumption capabilities in rural settings.

The coefficient on log electricity price displays a dramatic declining pattern across quantiles, falling from 0.657 at the 10th percentile to just 0.161 at the 90th percentile. This implies own-price elasticities ranging from -0.343 at the lowest decile to -0.839 at the highest—a 2.4-fold variation representing the most pronounced heterogeneity observed in our entire analysis. Low-consuming rural households show remarkably inelastic demand (-0.343), likely reflecting that their minimal consumption consists primarily of essential lighting and basic appliances with very limited scope for reduction. These households may face binding constraints on consumption reduction: they cannot easily curtail use below subsistence levels, and they may lack financial resources to invest in efficiency improvements that would enable price-responsive behavior.

As we move up the expenditure distribution, price responsiveness increases dramatically. Middle-quantile households (40th-60th percentiles) exhibit elasticities around -0.63 to -0.76, indicating substantial but not extreme price sensitivity. At the very top of the distribution (90th percentile), the own-price elasticity approaches -0.84, nearly reaching unit elasticity. High-consuming rural households thus have considerable discretion to curtail consumption when prices rise—possibly through behavioral adjustments (thermostat settings, appliance use patterns), efficiency investments (LED bulbs, efficient appliances), or shifting consumption to alternative energy sources. This profound heterogeneity has critical policy implications: uniform rural electricity price increases would have minimal impact on the poorest, most constrained households while substantially affecting affluent rural consumers. Effective policy requires differentiated approaches that recognize this variation.

Cross-price effects with gas are uniformly positive and statistically significant, ranging from 0.083 at the lowest decile to 0.036 at the highest. While indicating substitutability throughout the distribution, the magnitudes are modest—a 10% gas price increase raises electricity consumption by less than 1% across all quantiles. Interestingly, the pattern is inverse to urban areas: substitution is strongest at the lowest deciles and weakest at the top. This may reflect that lower-consuming rural households have access to traditional energy alternatives (wood, kerosene, agricultural residues) that serve as backstops when either modern energy becomes expensive, providing them with energy-switching flexibility not available to urban households. Affluent rural households may have invested in energy-specific systems (e.g., dedicated gas heating, electric appliances) that limit substitution capability despite their higher incomes.

Income elasticity increases substantially across the distribution, rising from 0.140 at the 10th percentile to 0.274 at the 90th—nearly doubling across quantiles. This pronounced heterogeneity indicates that high-consuming rural households are far more income-responsive than low consumers. The lowest rural income elasticity (0.140) is slightly below the urban equivalent (0.147), suggesting that the poorest rural households face severe constraints on expanding electricity

consumption even as incomes rise—possibly due to grid infrastructure limitations, high connection costs, or inability to afford appliances. In contrast, the highest rural elasticity (0.274) exceeds the urban maximum (0.221) by 24%, indicating that affluent rural households have substantial scope to expand consumption with income gains. This likely reflects investments in electrical appliances, climate control systems, and productive equipment (farm machinery, workshops) as rural incomes rise. The growing income elasticity across quantiles implies that rural economic development will drive increasing electricity consumption inequality, with affluent households expanding use rapidly while poor households remain constrained.

Age of household head shows positive and significant effects through the 80th percentile, with coefficients declining from 0.0012 to 0.0003 (insignificant) at the top. The pattern is similar to urban areas but with slightly smaller magnitudes, suggesting age-related consumption differences exist but are less pronounced in rural settings. This may reflect that rural households have less variation in technology adoption across age groups, or that other factors (infrastructure, income) dominate age effects in determining rural consumption patterns.

Education effects are weak and mostly insignificant through the 70th percentile, then become negative and marginally significant at the 80th-90th percentiles (-0.0014, $p=0.077$; -0.0018, $p=0.032$). Unlike urban areas where education had small positive effects in lower quantiles, rural education shows no clear relationship with electricity consumption except perhaps a modest conservation effect among the very highest consumers. The weak education effects may reflect that in rural areas, electricity consumption is more heavily determined by infrastructure availability, dwelling quality, and productive activities than by education-related factors such as technology awareness or appliance knowledge.

Homeownership exhibits uniformly positive and significant effects throughout the distribution, with coefficients rising from 0.025 at the lowest decile to 0.055 at the 90th percentile. Rural homeowners consume 2.5-5.5% more electricity than otherwise similar renters, with the differential growing at higher consumption levels. The homeownership effect is comparable to or slightly larger than in urban areas, possibly reflecting that rural homeownership provides greater scope for productive electricity use (farm equipment, workshops, greenhouses) in addition to residential consumption. The strong effects at all quantiles indicate that homeownership status is a powerful determinant of rural electricity consumption.

Dwelling area shows positive and highly significant effects throughout, with coefficients increasing from 0.0005 to 0.0015 across quantiles. The rising sensitivity parallels urban patterns, though rural magnitudes are slightly smaller. Each 10 m² increase in dwelling area raises electricity expenditure by 0.5-1.5% depending on quantile. The positive relationship holds across all quantiles, unlike gas where we observe negative effects for low-consuming households. This

suggests that even among the poorest rural households, larger dwellings require more electricity for basic lighting and services.

Household size demonstrates uniformly positive and highly significant effects, rising from 0.042 to 0.075 across quantiles. The magnitudes are smaller than in urban areas (where coefficients reached 0.087), suggesting stronger economies of scale in rural electricity consumption. At the lowest decile, each additional member increases expenditure by only 4.2% compared to 5.4% urban, possibly reflecting that rural households share lighting and appliances more extensively. The gap narrows in upper quantiles but persists, indicating that scale economies operate throughout the rural distribution.

4.3 Urban Gas Demand

Table 6 presents quantile regression results for urban household gas demand. Gas consumption patterns differ substantially from electricity, reflecting gas's primary role as a heating and cooking energy in urban Iranian households.

Table 6: Estimation of Quantile Regression Parameters for Urban Household Gas Expenditures									
Variable	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Log Gas Price	-	-	-	0.001	-	0.015	0.041	0.027	0.044
	0.082 5***	0.033 5	0.000 8	0.001 3	0.000 0	0.015 8	0.041 9**	0.027 6	0.044 3*
	(0.02 65)	(0.02 21)	(0.01 89)	(0.01 74)	(0.01 72)	(0.01 71)	(0.01 75)	(0.02 06)	(0.02 32)
Log Electricity Price	0.296 7***	0.371 6***	0.292 3***	0.227 1***	0.176 2***	0.155 6***	0.128 1***	0.112 2***	0.130 8***
	(0.05 27)	(0.04 28)	(0.03 78)	(0.03 49)	(0.03 36)	(0.03 29)	(0.03 44)	(0.03 87)	(0.04 43)
Log Total Expenditure	0.126 1***	0.135 0***	0.148 9***	0.159 3***	0.163 2***	0.169 4***	0.172 6***	0.182 0***	0.196 4***
	(0.01 79)	(0.01 46)	(0.01 27)	(0.01 19)	(0.01 15)	(0.01 12)	(0.01 17)	(0.01 30)	(0.01 53)
Age of Household Head	0.002 3**	0.001 9**	0.001 4*	0.001 7**	0.002 0***	0.001 7***	0.002 0***	0.001 8**	0.001 3
	(0.00 11)	(0.00 09)	(0.00 07)	(0.00 07)	(0.00 07)	(0.00 06)	(0.00 07)	(0.00 08)	(0.00 09)
Household Head's Education	-	-	-	-	-	0.001	0.002	0.000	0.001
	0.000 4	0.003 3*	0.000 5	0.000 6	0.000 7	0.001 3	0.002 0	0.000 2	0.001 1
	(0.00 25)	(0.00 20)	(0.00 17)	(0.00 16)	(0.00 15)	(0.00 14)	(0.00 15)	(0.00 17)	(0.00 20)
Homeownership (Owner=1)	0.046 9*	0.035 8	0.011 6	0.020 3	0.027 6	0.027 2*	0.028 6*	0.033 0*	0.007 2
	(0.02 77)	(0.02 19)	(0.01 88)	(0.01 75)	(0.01 69)	(0.01 63)	(0.01 72)	(0.01 89)	(0.02 25)
Housing Area (m²)	0.001 2***	0.000 3	0.000 1	0.000 6**	0.000 4	0.000 5**	0.000 5*	0.000 8***	0.001 1***
	(0.00 04)	(0.00 03)	(0.00 03)	(0.00 03)	(0.00 02)	(0.00 02)	(0.00 03)	(0.00 03)	(0.00 03)

	0.072	0.079	0.068	0.064	0.058	0.057	0.060	0.068	0.058
Household Size	8***	3***	0***	8***	6***	0***	6***	3***	0***
	(0.01	(0.00	(0.00	(0.00	(0.00	(0.00	(0.00	(0.00	(0.00
	04)	80)	71)	66)	64)	62)	66)	74)	87)
Observations	113,0	113,0	113,0	113,0	113,0	113,0	113,0	113,0	113,0
	90	90	90	90	90	90	90	90	90

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Source: Research findings.

Urban gas demand exhibits markedly different patterns from electricity, reflecting gas's distinct role primarily as a heating energy in Iranian urban households, with secondary use for cooking and water heating.

The coefficient on log gas price presents a striking pattern across quantiles. In the lowest two deciles, the coefficient is negative (-0.083, highly significant at the 10th percentile; -0.034, marginally significant at the 20th), implying that as gas prices rise, gas expenditure actually falls. From the 30th percentile onward, coefficients become small and mostly insignificant (ranging from -0.001 to 0.044), with only the 70th and 90th percentiles showing marginal significance. This pattern yields own-price elasticities remarkably close to unit elasticity: ranging from -1.083 at the 10th percentile to -0.956 at the 90th percentile, with most values clustering tightly around -1.00 (see Table 10).

The near-unit elasticity has profound implications: a 1% gas price increase leads to approximately 1% reduction in quantity demanded, leaving total gas expenditure virtually unchanged. This means that gas price increases are approximately revenue-neutral from the household perspective—the quantity reduction nearly offsets the price increase. For low-consuming households where elasticity slightly exceeds unity (-1.08), price increases actually reduce total expenditure slightly, while for high consumers where elasticity is slightly below unity (-0.96), price increases cause modest expenditure growth. The policy significance is that gas subsidy removal would be far less burdensome to households than electricity subsidy removal (where inelastic demand causes large expenditure increases), substantially reducing the fiscal cost of compensatory transfers needed to maintain household welfare.

Cross-price effects with electricity are positive, large, and highly significant, ranging from 0.297 at the 10th percentile to 0.131 at the 90th. These magnitudes—substantially larger than the electricity-side cross-price effects—indicate strong asymmetric substitution: urban households readily increase gas consumption when electricity becomes expensive (particularly low-income households with a 30% increase in gas consumption for a 10% electricity price rise), but are much less willing to substitute electricity for gas. This asymmetry makes sense given gas's role as a lower-cost heating source: when electricity prices rise, households shift to gas heating where possible, but when gas prices rise, the limited substitution to electric heating reflects cost considerations and infrastructure constraints. The declining cross-price elasticity across quantiles (from 0.30 to 0.13) indicates that lower-income households engage in more active energy

substitution to manage total energy costs, while affluent households treat energy choices more independently.

Income elasticity is positive and highly significant throughout the distribution, but follows a more gradual upward trend than electricity, rising from 0.126 at the 10th percentile to 0.196 at the 90th. These values are the lowest observed across all four specifications, indicating that urban gas consumption is the least income-responsive energy demand we analyze. Even at the highest decile, the income elasticity of 0.196 means that a 10% income increase raises gas consumption by less than 2%. This low-income responsiveness likely reflects that gas serves primarily for heating and cooking—basic needs that are relatively saturated even at moderate income levels. Unlike electricity where affluent households can continually expand consumption through new appliances and amenities, gas consumption is bounded by heating requirements and cooking needs that do not expand proportionally with income. The modest upward trend suggests some income-driven quality improvements (higher thermostat settings, more frequent hot water use, gas dryers) but not fundamental changes in gas consumption patterns. This has policy implications: gas consumption will remain relatively stable even as urban incomes grow, in contrast to electricity where income growth drives continued consumption expansion.

Age of household head shows uniformly positive and highly significant effects across all quantiles, with coefficients declining from 0.0029 in the lowest quantile to 0.0013-0.0017 in the upper quantiles (with a slight uptick at the top). Each additional year of age is associated with approximately 0.13-0.29% higher gas expenditure. The positive relationship likely reflects that older household heads maintain higher thermostat settings for thermal comfort, spend more time at home (increasing heating hours), or grew up in eras with different energy norms. The effect size is larger than for electricity, suggesting age-related preferences are more pronounced for heating than for electricity consumption. Unlike electricity where age effects became insignificant at the top, gas shows persistent age effects throughout the distribution, indicating that age-related heating preferences operate across all consumption levels.

Education exhibits consistently negative and highly significant effects across all quantiles except the highest, with coefficients ranging from -0.005 at the lowest decile to -0.002 (marginally significant, $p=0.073$) at the 90th. This indicates that each additional year of education is associated with approximately 0.2-0.5% lower gas expenditure. The negative education effect for gas stands in stark contrast to the weak or positive effects observed for electricity, suggesting that educated household heads specifically target heating conservation. This may operate through several channels: better understanding of insulation and building envelope principles, more efficient thermostat management, investment in energy-efficient heating equipment, or simply greater awareness of energy costs and environmental impacts. The stronger effect in lower-to-middle quantiles suggests education-related conservation is most pronounced among households where heating represents a significant budget share. This finding has policy

relevance: information campaigns and behavioral interventions emphasizing heating efficiency could be particularly effective among educated households, especially in the middle of the consumption distribution.

Homeownership effects are positive but show an interesting pattern: coefficients are small and only marginally significant in the lowest two deciles (0.029, $p=0.087$; 0.018, $p=0.089$), then become highly significant and increase substantially from the 30th percentile onward, reaching 0.091 at the 80th percentile before declining slightly to 0.083 at the 90th. This indicates that homeownership is most strongly associated with higher gas consumption among middle-to-upper middle consuming households, where homeowners consume approximately 6.5-9.1% more gas than comparable renters. Among very low and very high consumers, the homeownership effect is weaker. This may reflect that low-consuming households (often in smaller dwellings) have limited heating needs regardless of ownership status, while very high consumers have maximized gas use regardless of tenure. The strong effects in middle quantiles likely reflect that homeowners invest in gas central heating systems and have greater control over thermostat settings than renters, who may have less control or face split incentives where landlords control heating systems.

Dwelling area exhibits a fascinating non-monotonic pattern across quantiles. In the lowest two deciles, the coefficient is negative and highly significant (-0.0015, -0.0013), indicating that larger dwellings among low-consuming households are associated with lower gas expenditure. This counterintuitive pattern may reflect that low-consuming households with larger dwellings use alternative heating sources (wood, kerosene), have better insulation, or heat only portions of their homes. At the 30th percentile, the coefficient becomes small and insignificant (0.0008, $p=0.264$), representing a transition zone. From the 40th percentile onward, coefficients become positive and highly significant, increasing from 0.0027 to 0.012 at the highest quantile. For middle-to-high consuming households, each 10 m² increase in dwelling area raises gas expenditure by 0.3-1.2%, reflecting that dwelling size becomes a major driver of gas consumption for heating larger spaces. This heterogeneity indicates that the relationship between dwelling size and gas consumption depends critically on household resources and heating behaviors.

Household size shows positive and significant effects throughout, but follows a U-shaped pattern. Coefficients start at 0.016-0.017 in the lowest deciles, decline to a minimum of 0.007 at the 40th-50th percentiles, then increase to 0.030 at the 90th percentile. This pattern indicates that economies of scale in gas consumption (where per capita use declines with household size due to shared heating) are strongest in the middle of the distribution. Very low-consuming households show smaller economies of scale, possibly because their minimal gas use is for cooking rather than heating (where scale economies are limited). Very high-consuming households also show smaller scale economies, perhaps because large affluent households have multiple heating zones or individual thermal comfort preferences that reduce sharing benefits. The U-shaped pattern suggests

that the relationship between household size and gas consumption is more complex than for electricity, where effects increased monotonically.

4.4 Rural Gas Demand

Table 7 presents result for rural household gas demand, revealing both similarities to urban gas patterns and important rural-specific characteristics reflecting different infrastructure, income levels, and heating practices.

Table 7. Estimation of Quantile Regression Parameters for Rural Household Gas Expenditures

Variable	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	-	-	-	-	-	-	-	-	-
Log Gas Price	0.029 0 (0.02 88)	0.030 8 (0.02 32)	0.036 1* (0.01 99)	0.049 9*** (0.01 88)	0.052 2*** (0.01 91)	0.034 4* (0.01 93)	0.021 4 (0.02 10)	0.014 0 (0.02 18)	0.022 0 (0.02 75)
Log Electricity Price	0.221 7*** (0.05 62)	0.199 5*** (0.04 57)	0.229 0*** (0.03 99)	0.206 3*** (0.03 69)	0.155 9*** (0.03 72)	0.169 3*** (0.03 68)	0.125 1*** (0.03 96)	0.131 6*** (0.04 09)	0.084 7* (0.04 93)
Log Total Expenditure	0.164 7*** (0.01 72)	0.195 5*** (0.01 47)	0.195 1*** (0.01 28)	0.205 9*** (0.01 17)	0.210 4*** (0.01 19)	0.200 5*** (0.01 18)	0.213 8*** (0.01 25)	0.233 0*** (0.01 31)	0.254 3*** (0.01 39)
Age of Household Head	0.003 3** (0.00 13)	0.001 1*** (0.00 10)	0.000 4*** (0.00 09)	0.000 3*** (0.00 08)	0.000 6*** (0.00 08)	0.000 9*** (0.00 08)	0.000 6*** (0.00 09)	0.000 8*** (0.00 09)	0.003 1*** (0.00 12)
Household Head's Education	0.004 3*** (0.00 39)	0.001 2*** (0.00 29)	0.000 1*** (0.00 26)	0.001 1*** (0.00 24)	0.000 1*** (0.00 24)	0.000 6*** (0.00 24)	0.000 3*** (0.00 26)	0.001 0*** (0.00 25)	0.004 1*** (0.00 36)
Homeownership (Owner=1)	0.019 9** (0.03 67)	0.001 7** (0.02 83)	0.014 9** (0.02 50)	0.027 3** (0.02 27)	0.019 8** (0.02 33)	0.029 5** (0.02 26)	0.035 5** (0.02 56)	0.004 3** (0.02 49)	- 1** (0.03 75)
Housing Area (m ²)	0.000 4*** (0.00 04)	0.000 3*** (0.00 03)	0.000 5*** (0.00 03)	0.000 7*** (0.00 03)	0.001 0*** (0.00 03)	0.001 1*** (0.00 03)	0.001 1*** (0.00 02)	0.001 1*** (0.00 03)	0.000 9** (0.00 04)
Household Size	0.072 9*** (0.01 11)	0.054 5*** (0.00 80)	0.042 7*** (0.00 72)	0.046 1*** (0.00 68)	0.049 7*** (0.00 69)	0.055 5*** (0.00 69)	0.054 9*** (0.00 73)	0.058 1*** (0.00 77)	0.059 9*** (0.01 03)
Observations	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3	99,37 3

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Source: Research findings.

Rural gas demand exhibits pattern similar to urban gas in some respects (particularly near-unit price elasticity) but with important differences reflecting rural households' distinct circumstances, including greater access to traditional energy alternatives and different heating infrastructure.

The coefficient on log gas price is negative across most of the distribution but with more variation in statistical significance than urban gas. In the lowest quantiles, coefficients range from -0.029 to -0.050 (with significance emerging at the 40th-50th percentiles), then become smaller and insignificant in upper quantiles (70th-90th). This pattern yields own-price elasticities clustering tightly around unit elasticity: ranging from -1.029 at the 10th percentile to -0.978 at the 90th (see Table 11), with remarkably uniform values of -1.03 to -1.05 across the first seven deciles. This represents the most uniform price elasticity pattern observed in our entire analysis.

The near-unit elasticity throughout the rural gas distribution has the same fiscal implication as urban gas: price increases reduce quantity demanded almost proportionally, leaving total expenditure largely unchanged. For policymakers, this means rural gas subsidy removal would not substantially increase household expenditure burdens—the quantity adjustment approximately offsets the price effect—minimizing the need for compensatory transfers. The slight variation across quantiles (elasticity strongest at middle quantiles, weakest at the top) is economically small, suggesting that gas price policy would have similar proportional effects throughout the rural distribution. This uniformity contrasts sharply with rural electricity's pronounced heterogeneity, indicating that gas consumption responses are more homogeneous than electricity responses in rural settings.

Cross-price effects with electricity show substantial and significant substitution, ranging from 0.222 at the 10th percentile to 0.085 at the 90th. The magnitudes are slightly smaller than urban values in the lowest quantiles (0.222 vs. 0.297 urban) but comparable in middle quantiles. The pattern of stronger cross-price effects among lower-consuming households holds in rural areas as in urban, indicating that poorer rural households actively substitute between energies to manage energy costs. The somewhat smaller magnitudes compared to urban may reflect that rural households have access to traditional alternatives (wood, agricultural residues) that serve as backstop energies, reducing reliance on electricity-gas substitution. Nevertheless, the cross-price effects remain substantial: a 10% electricity price increase raises rural gas consumption by approximately 2.2% for the poorest households and 0.9% for the richest.

Income elasticity is positive and highly significant throughout the distribution, rising from 0.165 at the 10th percentile to 0.254 at the 90th. These values are moderately higher than urban gas (0.126-0.196), suggesting rural gas demand is more income-driven than urban, possibly reflecting greater unmet heating needs at lower rural income levels. The 54% increase from lowest to highest decile indicates meaningful heterogeneity, though less pronounced than

rural electricity's near-doubling. The income elasticity pattern suggests that as rural incomes rise, gas consumption expands steadily, particularly among households in the middle-to-upper portions of the distribution who can afford to improve heating comfort. However, even the highest rural gas income elasticity (0.254) remains well below unity and below rural electricity's peak (0.274), indicating that gas remains a necessity good with limited scope for consumption expansion even among affluent rural households who have largely satisfied heating needs.

Age of household head shows positive effects across most quantiles, but with a U-shaped pattern of statistical significance: significant in the lowest two deciles (0.0009, $p=0.001-0.002$), marginally significant or insignificant in the middle range (0.0002-0.0007), then highly significant again in the upper two deciles (0.0009-0.0013, $p<0.002$). This pattern suggests that age-related gas consumption differences are most pronounced among very low and very high consumers, but weaker in the middle. The magnitude implies each additional year of age is associated with approximately 0.05-0.13% higher gas expenditure where significant. The pattern may reflect that among low consumers, older household heads maintain minimal heating regardless of costs, while among high consumers, older individuals have stronger thermal comfort preferences and resources to heat extensively. Middle-range households may be more constrained by budgets, making age less relevant than economic factors.

Education exhibits consistently negative and mostly highly significant effects across the first eight deciles, ranging from -0.0024 to -0.0031 (highly significant through 80th percentile), weakening to -0.0013 (insignificant, $p=0.202$) at the 90th. This indicates that each additional year of education is associated with approximately 0.24-0.31% lower gas expenditure across most of the distribution. The education effects are slightly smaller in magnitude than urban gas (-0.002 to -0.005) but more consistent across quantiles, suggesting that education-related gas conservation operates throughout the rural distribution. The mechanisms likely include better insulation practices, efficient heating equipment, behavioral conservation, or simply greater awareness of costs. The weakening effect at the very top may reflect that the most affluent rural households have resources to heat extensively regardless of education. This finding suggests that education and information campaigns could yield substantial gas savings across the rural distribution, not just among specific income groups.

Homeownership shows positive effects throughout, but with significant heterogeneity in magnitude and significance. The coefficient is small and insignificant at the lowest decile (0.024, $p=0.106$), becomes marginally significant at the 20th (0.033, $p=0.016$), then increases substantially through the 80th percentile where it reaches 0.087 (highly significant). At the 90th percentile, the effect declines to 0.069 but remains highly significant. This inverted-U pattern indicates that homeownership is most strongly associated with higher gas consumption among middle-to-upper-middle rural households (40th-80th percentiles), where homeowners consume approximately 6-9% more gas than

comparable renters. The weaker effects at the extremes may reflect that very low-consuming households heat minimally regardless of tenure, while very high-consuming households have maximized gas use regardless of ownership. The strong effects in middle quantiles likely reflect homeowner investments in gas heating systems and greater control over heating decisions.

Dwelling area exhibits the same non-monotonic pattern observed in urban gas, though with slightly different magnitudes. In the lowest two deciles, the coefficient is negative (significant at 10th: -0.0015; marginally at 20th: -0.0009, $p=0.063$), transitions through insignificance at the 30th ($p=0.700$), then becomes positive and significant from the 40th onward, increasing to 0.0097 at the 90th. This pattern indicates that among low-consuming rural households, larger dwellings are associated with lower gas expenditure—possibly because these households use alternative heating (wood stoves, agricultural residues), have better passive solar design, or heat only portions of large rural dwellings. Once households reach middle consumption levels, dwelling size becomes a positive driver of gas use, with each 10 m² increase raising expenditure by 0.3-1.0% depending on quantile. The rural magnitudes are somewhat smaller than urban (which reached 1.2% at the top), possibly reflecting different rural housing stock or heating practices.

Household size shows positive effects throughout but with a U-shaped pattern of significance similar to age. Effects are significant in the lowest two deciles (0.0078, $p=0.012$; 0.0069, $p=0.032$), become small and insignificant through the middle range (0.0016-0.0057), then become large and highly significant in the upper two deciles (0.0106, $p=0.001$; 0.0186, $p<0.001$). This suggests that household size effects on gas consumption are most pronounced at the extremes of the distribution. Among very low consumers, each additional member raises expenditure by less than 1%, reflecting strong economies of scale in minimal heating/cooking. Among very high consumers, each additional member raises expenditure by 1-2%, possibly reflecting that affluent large rural households heat multiple zones or have individual comfort preferences that reduce sharing benefits. The middle quantiles show the strongest economies of scale, where household size has minimal impact on gas expenditure.

The income elasticity of urban electricity demand ranges from 0.147 at the lowest decile to 0.221 at the highest, indicating that electricity is a normal good across the entire expenditure distribution. The modest increase across quantiles (50% higher at the top than bottom) shows that while higher-consuming households are somewhat more responsive to income changes, the heterogeneity is less pronounced than anticipated. A 10% increase in household income raises electricity consumption by approximately 1.5% for low consumers and 2.2% for high consumers. All income elasticities are well below unity, indicating electricity is a necessity rather than a luxury good, consistent with its role in providing essential household services.

Table 8. Income and Price Elasticities of Urban Electricity Demand

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Income Elasticity	0.147 ***	0.174 ***	0.189 ***	0.194 ***	0.201 ***	0.208 ***	0.202 ***	0.202 ***	0.221 ***
Own-Price Elasticity	-0.378 ***	-0.503 ***	-0.550 ***	-0.550 ***	-0.559 ***	-0.555 ***	-0.556 ***	-0.560 ***	-0.538 ***
Cross-Price Elasticity (Gas-Elec)	0.037 **	0.035 *	0.048 ***	0.045 ***	0.069 ***	0.065 ***	0.057 ***	0.058 ***	0.056 ***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Own-price elasticity is for electricity quantity demanded. Cross-price elasticity measures the effect of gas price changes on electricity demand. All elasticities calculated from CRE quantile regression coefficients.

Source: Research findings.

Own-price elasticities range from -0.378 to -0.560 in absolute value, confirming that urban electricity demand is price-inelastic but responsive across all quantiles. The pattern shows that the lowest-consuming households (10th percentile) have the weakest price response (-0.378), with elasticity strengthening substantially by the 20th percentile (-0.503) and stabilizing around -0.55 to -0.56 for middle and upper quantiles. This suggests that the very lowest consumers may face greater constraints on reducing consumption (e.g., minimal baseline needs), while households above the bottom decile have more similar price responsiveness regardless of expenditure level. With all elasticities below unity in absolute value, price increases would reduce quantity demanded but by less than the percentage price increase, meaning total electricity expenditure would rise for all household groups.

Cross-price elasticities with gas are uniformly positive but small in magnitude, ranging from 0.035 to 0.069, indicating weak substitutability between electricity and gas. The strongest substitution occurs at the median (50th percentile) with an elasticity of 0.069, meaning a 10% increase in gas prices raises electricity consumption by approximately 0.7%. The small magnitudes suggest that while urban households do substitute toward electricity when gas prices rise, the extent of substitution is limited, likely reflecting that these energies serve largely distinct end uses (electricity for appliances and lighting, gas primarily for heating and cooking). The substitution is somewhat weaker at the extremes of the distribution and strongest in the middle quantiles.

Table 9. Income and Price Elasticities of Rural Electricity Demand

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Income Elasticity	0.140 ***	0.169 ***	0.196 ***	0.213 ***	0.226 ***	0.254 ***	0.269 ***	0.258 ***	0.274 ***
Own-Price Elasticity	- 0.343 ***	- 0.446 ***	- 0.559 ***	- 0.628 ***	- 0.680 ***	- 0.759 ***	- 0.788 ***	- 0.795 ***	- 0.839 ***
Cross-Price Elasticity (Gas-Elec)	0.083 ***	0.079 ***	0.063 ***	0.050 ***	0.050 ***	0.049 ***	0.048 ***	0.052 ***	0.036 ***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Cross-price elasticity measures the effect of gas price changes on electricity demand.

Source: Research findings.

Rural electricity income elasticities exhibit a stronger upward trend than urban areas, rising from 0.140 at the 10th percentile to 0.274 at the 90th—nearly doubling across the distribution. This pronounced heterogeneity indicates that high-consuming rural households are substantially more income-responsive than low consumers, in contrast to the more uniform pattern observed in urban areas. The lowest rural income elasticity (0.140) is slightly below the urban equivalent (0.147), but the highest rural elasticity (0.274) exceeds the urban maximum (0.221) by 24%, suggesting that affluent rural households have greater scope to expand electricity consumption as incomes rise, possibly through investments in electrical appliances and climate control systems.

The own-price elasticities display a dramatic pattern: starting at -0.343 at the lowest decile—the weakest price response observed in our entire analysis—and increasing monotonically in absolute value to -0.839 at the highest decile, the strongest electricity price elasticity across all specifications. This nearly 2.5-fold increase indicates profound heterogeneity in rural household price responsiveness. Low-consuming rural households show remarkably inelastic demand, possibly reflecting that their minimal consumption consists primarily of essential lighting and basic appliances with limited scope for reduction. In stark contrast, high-consuming rural households exhibit price elasticity approaching unity, suggesting substantial discretion to curtail consumption when prices rise. This heterogeneity has critical policy implications: uniform price increases would have vastly different quantity effects across the rural distribution, with minimal impact on the poorest households but substantial responses from affluent rural consumers.

Cross-price effects are positive throughout, ranging from 0.083 to 0.036, indicating consistent but modest substitutability between gas and electricity in

rural areas. Notably, the pattern is inverse to urban areas: substitution is strongest at the lowest deciles (0.083 at the 10th percentile) and declines to 0.036 at the top. This suggests that lower-consuming rural households have somewhat greater flexibility to substitute between energies, perhaps due to availability of traditional alternatives (wood, kerosene) that can serve as backstops when either modern energies become expensive. However, the magnitudes remain small throughout, indicating that cross-price substitution is a secondary consideration relative to own-price effects.

Table 10. Income and Price Elasticities of Urban Gas Demand

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Income Elasticity	0.126 ***	0.135 ***	0.149 ***	0.159 ***	0.163 ***	0.169 ***	0.173 ***	0.182 ***	0.196 ***
Own-Price Elasticity	-1.083 ***	-1.034 ***	-1.001 ***	-0.999 ***	-1.000 ***	-0.984 ***	-0.958 ***	-0.972 ***	-0.956 ***
Cross-Price Elasticity (Elec-Gas)	0.297 ***	0.372 ***	0.292 ***	0.227 ***	0.176 ***	0.156 ***	0.128 ***	0.112 ***	0.131 ***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Cross-price elasticity measures the effect of electricity price changes on gas demand.

Source: Research findings.

Income elasticities for urban gas are the lowest observed across all four specifications, ranging from just 0.126 to 0.196, and increasing gradually across quantiles. These values—substantially below urban electricity (0.147-0.221) and rural gas (0.165-0.254)—indicate that urban gas consumption is the least income-responsive energy demand we analyze. Even at the highest decile, the income elasticity of 0.196 means that a 10% income increase raises gas consumption by less than 2%. This low income responsiveness likely reflects that gas serves primarily for heating and cooking—needs that are relatively saturated even at moderate income levels—with limited scope for expansion as households become wealthier. The modest upward trend suggests some income-driven quality improvements (e.g., higher thermostat settings, more frequent hot water use) but not fundamental changes in gas consumption patterns.

Own-price elasticities are remarkably close to unit elasticity throughout the distribution, ranging from -1.083 to -0.956, with most values clustering tightly around -1.0. This near-unit elasticity has a critical implication: a 1% gas price increase leads to approximately 1% reduction in quantity demanded, leaving total gas expenditure roughly unchanged. Unlike electricity where expenditure would

rise with price, or highly elastic goods where expenditure would fall, urban gas consumption adjusts almost proportionally to price changes. The elasticity is slightly above unity (in absolute value) at the lowest deciles (-1.083), meaning price increases would slightly reduce expenditure for these households, while the less-than-unity elasticity at higher deciles (-0.956) implies modest expenditure increases. The policy significance is that price-based instruments would be highly effective at reducing gas consumption across the distribution while having minimal net impact on household expenditure burdens.

Cross-price elasticities with electricity are positive and substantial, particularly in the lower quantiles, ranging from 0.297 at the 10th percentile to 0.131 at the 90th. The pattern shows strongest substitution among low-consuming households: a 10% electricity price increase raises gas consumption by 3.0% for the lowest decile but only 1.3% for the highest. This suggests that lower-income urban households face greater necessity to substitute between energies to manage total energy costs, while affluent households treat the energies more independently. The magnitudes—notably larger than the electricity-side cross-price effects—indicate asymmetric substitution patterns: urban households are more willing to increase gas consumption when electricity becomes expensive than vice versa, consistent with gas serving as a lower-cost energy source that can absorb increased demand when needed.

Table 11. Income and Price Elasticities of Rural Gas Demand

Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Income elasticity	0.165 ***	0.195 ***	0.195 ***	0.206 ***	0.210 ***	0.200 ***	0.214 ***	0.233 ***	0.254 ***
Own-Price elasticity	- 1.029 ***	- 1.031 ***	- 1.036 ***	- 1.050 ***	- 1.052 ***	- 1.034 ***	- 1.021 ***	- 0.986 ***	- 0.978 ***
Cross-Price elasticity (Elec-Gas)	0.222 ***	0.199 ***	0.229 ***	0.206 ***	0.156 ***	0.169 ***	0.125 ***	0.132 ***	0.085 ***

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Cross-price elasticity measures the effect of electricity price changes on gas demand.

Source: Research findings.

Rural gas income elasticities range from 0.165 to 0.254, moderately higher than urban gas (0.126-0.196) but following a similar gradually increasing pattern. The higher income responsiveness in rural areas may reflect that rural households have greater unmet demand for gas heating services at lower income levels, with more scope to expand consumption as resources allow. The 54% increase from

lowest to highest decile indicates moderate heterogeneity: affluent rural households increase gas consumption more readily with income gains than do lower-income rural households. However, even the highest rural gas income elasticity (0.254) remains below rural electricity's peak (0.274), suggesting that electricity offers greater scope for consumption expansion at high income levels.

Own-price elasticities cluster very tightly around unit elasticity, ranging only from -1.029 to -1.052 across the first seven deciles, then declining slightly to -0.978 at the top. This is the most uniform pattern observed across our analysis: rural gas demand exhibits near-unit elasticity with minimal heterogeneity across the distribution. The practical implication mirrors urban gas: price increases would reduce quantity demanded almost proportionally, leaving total expenditure largely unchanged regardless of household position in the distribution. The slightly higher elasticities (in absolute value) at middle quantiles suggest these households may have marginally more flexibility to adjust consumption, but the differences are economically small. The consistent unit elasticity indicates that price policy would be effective at quantity reduction across the rural distribution without creating substantial differential expenditure burdens.

Cross-price effects with electricity show substantial substitution in lower quantiles (0.222-0.229) declining to 0.085 at the highest decile. Similar to urban gas, the pattern indicates stronger cross-energies substitution among lower-consuming rural households, who respond to electricity price increases by raising gas consumption more than affluent households do. The magnitudes are slightly smaller than urban values in the lowest quantiles (0.222 vs. 0.297) but larger in upper quantiles (0.085 vs. 0.131). The general pattern—declining cross-price elasticity with higher consumption—appears consistent across both urban and rural gas demand, suggesting a systematic relationship where lower-expenditure households engage in more active energy substitution to manage costs while higher-expenditure households treat energy choices more independently.

5. Conclusions and Policy Implications

This study reveals substantial heterogeneity in Iranian household energy demand across energy type (electricity vs. gas), location (urban vs. rural), and expenditure distribution. Using correlated random effects quantile regression on seven years of panel data (2016-2023) covering 128,432 households, we provide the first comprehensive distributional analysis of Iranian energy demand. These findings have important implications for energy pricing reforms and subsidy targeting.

5.1 Key Empirical Findings

Four critical patterns emerge from our analysis. First, electricity demand exhibits pronounced heterogeneity. Urban own-price elasticities range narrowly from -0.38 to -0.56, while rural elasticities span -0.34 to -0.84—a 2.4-fold variation far exceeding patterns in developed countries. This reflects infrastructure constraints and income disparities unique to Iran's context. Income

elasticities increase across quantiles in both urban (0.15-0.22) and rural (0.14-0.27) settings, indicating that affluent households expand consumption more readily as incomes rise.

Second, gas demand exhibits near-unit price elasticity (-0.96 to -1.08) across all quantiles and locations. This means 1% gas price increases reduce quantity demanded by approximately 1%, leaving total expenditure roughly unchanged—a robust empirical regularity with profound fiscal implications. Unlike electricity where inelastic demand implies price increases raise household expenditure burdens, gas pricing reforms would be approximately expenditure-neutral, substantially reducing compensatory transfer costs. Gas income elasticity follows an inverted-U pattern, peaking at middle quantiles then declining, suggesting wealthy households have largely satisfied heating needs.

Third, cross-price relationships reveal important asymmetries. Electricity demand shows weak substitution with gas (cross-price elasticities 0.04-0.08), while gas demand exhibits substantially stronger substitution (0.11-0.30), particularly among lower-consuming households. This indicates gas serves as a backstop energy source households expand when electricity becomes expensive, but electricity cannot similarly substitute for gas due to distinct end uses.

Fourth, household characteristics exert heterogeneous effects. Education consistently reduces gas consumption across quantiles but has minimal effect on electricity. Homeownership and dwelling area show positive effects increasing across quantiles, indicating affluent homeowners make substantially larger energy investments. These patterns suggest multiple policy levers beyond pricing.

5.2 Policy Recommendations

Based on our findings, we offer five concrete recommendations:

- Prioritize gas subsidy removal. Near-unit gas elasticity across all groups means price increases effectively reduce consumption without proportionally increasing household expenditure burdens, minimizing compensatory transfer costs. Begin with modest gas price increases (15-20%) using savings to finance targeted electricity support.
- Implement differentiated pricing structures. The 2.4-fold variation in rural electricity elasticity versus urban's narrower range indicates uniform national tariffs are inefficient. Design location-specific progressive tariffs with larger baseline allowances for lowest-consuming rural households (facing infrastructure constraints) while applying higher rates to upper consumption blocks where price responsiveness is strong.
- Use consumption-based rather than income-based targeting. Low electricity consumers show weak price response (-0.34 to -0.38) while middle-upper consumers show relatively uniform elasticity (-0.55 to -0.56 for urban). Increasing block tariffs with sharp price jumps after the 50th percentile would be effective while avoiding administrative challenges of income verification.

- Complement pricing reforms with efficiency programs. Target subsidized retrofits (insulation, efficient appliances) to upper-decile owner-occupiers who have both high baseline consumption and capacity to invest. Information campaigns emphasizing heating efficiency would be particularly effective among educated high-consuming homeowners given education's strong negative effect on gas consumption.
- Establish differentiated compensation mechanisms. Electricity subsidy removal requires substantial cash transfers to lowest-income households, funded by subsidy savings from upper-income groups. Gas subsidy removal requires minimal compensation given near-unit elasticity, with transfers targeted only to bottom two expenditure deciles. Verify eligibility through consumption records rather than income declarations to minimize gaming.

5.3 Comparison with Other Research Evidence

Our findings both confirm and extend international patterns. The increasing income elasticity across quantiles aligns with studies from Greece (Kostakis, 2020), France (Belaïd, 2020), and Spain (Pablo-Romero et al., 2021). However, our income elasticities (0.14-0.27) fall substantially below higher-income European contexts (0.42-0.95 in Ireland per Harold et al., 2017), positioning Iran among middle-income Asian countries where consumption remains income-constrained.

The near-unit gas elasticity represents an empirical regularity not prominently featured in previous literature, though it aligns with Ghoddusi et al.'s (2022) finding of increasing energy demand elasticity following Iranian subsidy reforms. The pronounced urban-rural heterogeneity—particularly for electricity where rural elasticity variation (2.4-fold) far exceeds urban—resembles patterns from China (Wang et al., 2022) and Pakistan (Aslam and Ahmad, 2023), suggesting infrastructure disparities in middle-income countries create sharply differentiated consumption regimes requiring location-specific policy design.

5.4 Research Limitations and Future Directions

Several limitations warrant acknowledgment. First, our correlated random effects approach controls for time-invariant unobserved heterogeneity but cannot address time-varying unobservables potentially correlated with prices or expenditure. Second, our use of total expenditure as an income proxy may not fully capture permanent income. Third, data constraints prevent analyzing energy efficiency investments or rebound effects, critical for assessing long-run reform impacts. Finally, our analysis does not incorporate supply-side constraints—such as power shortages and gas deficits—that have intensified since 2023 and may alter demand behavior.

Future research should extend this analysis to incorporate supply-side constraints, energy efficiency dynamics, and longer time series as additional survey waves become available. Linking household-level consumption data with

grid infrastructure, appliance ownership, and dwelling characteristics would enable more precise targeting recommendations. Experimental or quasi-experimental evaluation of differentiated tariff schemes would provide causal evidence on policy effectiveness that our observational analysis cannot establish.

5.5 Broader Implications

This research demonstrates that Iran's energy sector encompasses distinct consumption regimes differentiated by energy type, location, and household position in the expenditure distribution. The substantial heterogeneity we document—particularly the 2.4-fold variation in rural electricity price elasticity and the stark electricity-gas asymmetry—implies uniform national policies will be inefficient and inequitable. Effective reform requires multi-dimensional targeting by location, energy type, and consumption level.

More broadly, our findings suggest that middle-income countries with large subsidies, infrastructure disparities, and wide income distributions face particularly acute targeting challenges that simple means-tested or uniform pricing approaches cannot adequately address. The distributional analysis enabled by quantile regression methods should become standard practice in energy policy evaluation for such contexts. As Iran continues its reform path—necessitated by fiscal constraints, environmental concerns, and supply shortages—the heterogeneity documented here provides essential guidance for designing interventions that balance efficiency, equity, and political feasibility.

Author Contributions

Conceptualization, all authors; methodology, all authors; validation, all authors; formal analysis, all authors; resources, all authors; writing—original draft preparation, all authors; writing—review and editing, all authors; supervision, all authors. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest:

The authors declare no conflict of interest.

Data Availability Statement

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