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A Demand Systems Analysis of Energy Sources in the United States

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ABSTRACT

This study estimates a Generalized Exact Affine Stone Index model to quantify demand structure among such energy sources as natural gas, coal, nuclear, wind, solar, and geothermal energy, employing monthly time-series data ranging from January of 2009 through December of 2020. The demand for natural gas, coal, and nuclear energy emerges as inelastic. A significant substitutability relationship is empirically established between the energy sources. All the computed expenditure elasticities are positive, with natural gas being the most sensitive and nuclear energy being the least sensitive to energy source expenditures. Pre-committed consumption is found for geothermal energy. Finally, the welfare implications of the projected decrease in the natural gas price are assessed with the Hicksian compensating variation measure.

Keywords: Energy Sources Demand, Generalized Exact Affine Stone Index Demand Model, Pre-Committed Energy Demand
JEL Classifications: Q41, Q42

1. INTRODUCTION

The U.S. is experiencing major changes in its energy landscape, affected by evolving consumption patterns, technological advancements, and policy shifts. In 2023, total U.S. primary energy consumption reached 93.59 quadrillion British thermal units, with petroleum accounting for the largest share at 38%, followed closely by natural gas at 36%. Nuclear electric power and coal each contributed 9% to the total. Renewable energy also made up 9% of the overall consumption, and within this category, the breakdown was as follows: geothermal energy accounted for 1%, solar energy 11%, wind energy 18%, biomass waste 5%, biofuels 32%, and wood 23% (U.S. Energy Information Administration, 2024). These numbers are indicative of the U.S. heavy dependence on fossil fuels (petroleum and natural gas) for its energy needs. At the same time, renewable energy sources, while growing, accounted for about 9% of total consumption, marking the ongoing transition towards cleaner energy sources (U.S. Energy Information Administration, 2024).

One of the major factors influencing the energy market is the electrification trends in transportation, heating, and industry (Peoples Company, 2024). The Energy Information Administration predicts record levels of electricity consumption through 2024 and 2025, thus putting a lot of pressure on energy systems (U.S. Energy Information Administration, 2025). At the same time, the U.S. energy system has to deal with several important challenges concerning demand, reflecting both structural pressures and evolving consumption dynamics. In their turn, these challenges impact grid reliability, affordability, sustainability, and the effectiveness of future policy and infrastructure investments (U.S. Department of Energy, 2024). In light of these developments, a detailed study of energy demand across different sources gains utmost importance, since such research can shed light on underlying drivers of consumption, predict future trends, and guide public and private sector decision-making. Additionally, a thorough understanding of energy demand also allows for a better integration of renewable sources, diminishes reliance on volatile fossil fuel markets, and helps mitigate the economic and environmental risks associated with energy transitions.

A significant effort has been dedicated to studying demand for energy sources with the estimation of demand elasticities by employing various modeling techniques. Some of the initial surveys of the energy demand literature were conducted by Taylor (1977), Bohi and Zimmerman (1984), Abodunden et al. (1985), and Dahl (1993). In addition, numerous studies have examined demand across different types of energy sources: Gasoline (Dahl and Sterner, 1991; Archibald and Gillingham, 1980), natural gas (Balestra and Nerlove, 1966; Al-Sahlawi, 1989), electricity (Acton et al., 1980; Archibald et al., 1982; Badri, 1992).

At the same time, several recent studies offer comprehensive and systematic overviews of energy demand, each emphasizing different analytical dimensions. For instance, Verwiebe et al. (2021) conduct a structured literature review that highlights a wide range of modeling approaches used in the analysis of energy demand. Similarly, Labandeira et al. (2016) provide a meta-analysis focusing on the determinants of energy demand by estimating both short-run and long-run price elasticities. Adding to this body of work, Mjelde and Duangnate (2023) present a systematic review that specifically examines the role of pre-committed quantities in the context of energy commodities. Together, all of these studies contribute valuable insights into the evolving methodologies and key drivers shaping energy demand research.

Two prior studies that are similar to the present analysis in the use of time-series data to examine demand for various energy sources in a formal demand system framework while accounting for pre-committed consumption are the ones by Rowland et al. (2017) and Bakhtavoryan et al. (2025). In particular, Rowland et al. (2017) estimated linear approximation of the Generalized Almost Ideal Demand System (LA-GAIDS) and Almost Ideal Demand System (LA-AIDS) models using time-series data on oil, natural gas, and coal from 1980 to 2014 to study the implications of including the pre-committed consumption levels. They found the own-price elasticities from both specifications to be negative with the demand being elastic for oil and natural gas and inelastic for coal for the LA-GAIDS demand model and inelastic for oil, natural gas, and coal for the LA-AIDS model. All the statistically significant compensated cross-price elasticities were positive, indicative of the substitutability relationship. Also, all the computed expenditure elasticities for both the LA-GAIDS and LA-AIDS specifications were found to be positive and statistically significant. Finally, the study concludes that the inclusion of the pre-committed consumption levels contributes to better explaining energy demand in the U.S.

Bakhtavoryan et al. (2025) estimated a GEASI model to analyze the demand for natural gas, electricity, petroleum, solar energy, and wood in light of changing solar prices, using state-level data from 2012 to 2021. The estimation results reveal an elastic demand for natural gas, electricity, and solar energy, and an inelastic demand for petroleum and wood. Also, net substitutability relationship among the energy sources was empirically confirmed based on the compensated cross-price elasticities of demand. Natural gas emerged as the most expenditure elastic energy source and wood was found to be the least expenditure elastic energy source, with all the computed expenditure elasticities being positive and statistically significant. Finally, statistically significant pre-committed quantities were found for natural gas, electricity, and wood.

Similar to prior studies, the present analysis aims to purvey more insights into the demand structure of energy sources. However, it also adds to the extant literature by making the following distinct contributions. First, this study is distinctive as it represents the first empirical analysis of energy demand to incorporate a broad set of energy sources, including natural gas, coal, nuclear, wind, solar, and geothermal energy, thereby extending previous research by including nuclear and geothermal energy, which had not been considered before in a formal GEASI demand systems framework. Second, the application of the GEASI demand model allows for pre-committed consumption of energy sources, which, to the best of our knowledge, is the first empirical attempt with respect to nuclear and geothermal energy.

While the study by Bakhtavoryan et al. (2025) used the "levelized cost of energy" (LCOE)[1] as a price proxy exclusively for solar energy, the application of LCOE as a price proxy for all energy sources is the third distinguishing feature of the present study. This approach puts the prices of all considered energy sources on an equal footing, allowing for more consistent and comparable analysis across the energy spectrum. Furthermore, it needs to be noted that the LCOEs permits the comparison of different technologies (e.g., wind, solar, natural gas) of unequal life spans, project size, different capital cost, risk, return, and capacities (U.S. Department of Energy, 2017).

Fourth, unlike previous similar studies, this study explicitly accounts for seasonality in the consumption of energy sources. Seasonality is important because energy demand patterns vary significantly across seasons due to changes in weather, heating and cooling needs, and daylight hours. Fifth, using the empirical results from the present analysis, this study assesses the welfare effects of the projected decline in natural gas prices by calculating the compensating variation, an exercise, which, to the best of our knowledge, has not been done in previous research.

Overall, the present study seeks to accomplish the following objectives: (1) estimate the GEASI demand model to quantify the demand structure for energy sources with the "best" polynomial degree structure for real expenditures in place; (2) estimate uncompensated and compensated own-price and cross-price as well as expenditure elasticities of demand for an extensive set of energy sources; (3) compute pre-committed quantities in consumption; and (4) evaluate the welfare implications of the forecasted reduction in the natural gas price by computing compensating variation.

The estimation results obtained from this analysis will be of significance to various stakeholders. These include energy source manufacturers and retailers who can use price elasticities to put together a short-run revenue-maximizing pricing strategy as

1 LCOE is computed as lifetime costs divided by energy production (U.S. Department of Energy, 2017).

well as plan their inventory management and input procurement efficiently, in the presence of changing prices of competing energy sources. Also, energy supply operators (for example, gas supply operators) can use price elasticates to forecast revenue in an attempt to make decisions concerning capital investments and supply infrastructure improvements. Policymakers have a vested interest in the estimation results since they can utilize them to design or update relevant policies that provide oversight to the energy industry. Additionally, upon having a clear understanding of the precommitted portion of demand, policymakers can adjust resource allocation for infrastructure development to better meet the long-run needs of specific energy sources. Moreover, policymakers can devise and tailor subsidies or tax incentive programs to provide support to emerging energy sources with low precommitted demand. Finally, policymakers can utilize information on the compensating variation associated with the natural gas price reduction to evaluate its welfare consequences.

This study is divided into sections as follows. Next section presents the methodology related to the utilized GEASI demand framework. The subsequent section covers the data employed in this study. The following section supplies and discusses the estimation results. The last section contains summary, implications, and recommendations for future research.

2. METHODOLOGY: THE GENERALIZED EXACT AFFINE STONE INDEX (GEASI) DEMAND MODEL

We specify the GEASI demand model by Hovhannisyan and Shanoyan (2019) to empirically examine the demand for energy sources. In addition to possessing the benefits of widely used Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980), the EASI demand model presents additional desirable features related to permitting an unrestricted structures of Engel curve and unobserved consumer heterogeneity (Lewbel and Pendakur, 2009; Pendakur, 2009). Given the use of time-series data, in this study the final specification of the GEASI model is adjusted for first-order serial correlation. As a result, the estimated GEASI demand model looks as follows:

$$w_{it} = \frac{\tilde{c}_i p_{it}}{X} + \left(1 - \frac{\tilde{c}'p}{X}\right)\left(\begin{array}{l}\sum_{l=0}^{L} \beta_{il} (ln\left(X - \tilde{c}'p\right) - \\ w'lnp)^l + \sum_{k=1}^{N} \alpha_{ik} lnp_{kt}\end{array}\right) + \rho\left(w_{it-1}\right) -$$
$$\rho\left(\frac{\tilde{c}_i p_{it-1}}{X_{t-1}} + \left(1 - \frac{\tilde{c}' p_{t-1}}{X_{t-1}}\right)\left(\begin{array}{l}\sum_{l=0}^{L} \beta_{il} (ln\left(X_{t-1} - \tilde{c}' p_{t-1}\right) \\ -w'lnp_{t-1})^l + \sum_{k=1}^{N} \alpha_{ik} lnp_{kt-1}\end{array}\right)\right)$$
$$+ + \varepsilon_{it}, i = 1,\ldots,N; t = 1,\ldots,T, \quad (1)$$

Where w_{it} denotes the budget share of energy source i in period t, $\tilde{c}_i$ denotes the pre-committed demand level of energy source i, X denotes total energy source expenditures, p_{it} denotes the price of energy source i in period t, L denotes the highest order of polynomial in expenditures, $(ln\left(X - c'p\right) - w'lnp)$ denotes price and pre-commitment adjusted total expenditure that allows for the effects of real income, $\tilde{c}'p$ denotes pre-committed expenditures, ρ denotes the first-order serial correlation coefficient, t-1 subscript indicates the first lag, ε_{it} represents the error term, and α_{ik} and β_{il} denote the parameters to be estimated. We estimate the GEASI model in (1) with the classical theoretical restrictions of adding-up $\sum_{i=1}^{N}\beta_i = 1; \sum_{i=1}^{N}\beta_{il} = 0, \forall l = 1,\ldots,L; \sum_{i=1}^{N}\alpha_{ik} = 0, \left(\forall k = 1,\ldots,N\right)$, and symmetry $\alpha_{ik} = \alpha_{ki}$ ($\forall i, k = 1,\ldots = N$) in place.

Following Pollak and Wales (1981), we include quarterly seasonal dummy variables (Q_{1t}, Q_{2t}, and Q_{3t}) through a demographic translation procedure via the pre-committed demand as follows:

$$\tilde{c}_i = c_{i0} + c_{i1}Q_{1t} + c_{i2}Q_{2t} + c_{i3}Q_{3t} \quad (2)$$

Price elasticities of demand as well as expenditure elasticities are calculated using the formulas provided by Hovhannisyan and Shanoyan (2019). The compensated (or Hicksian) price elasticities (e_{ij}^H) from the GEASI model is given by:

$$e_{ij}^H = \frac{1}{w_i}\left(\frac{c_i p_i}{X} - \frac{c_i p_i}{X} A + \left[1 - \frac{c'p}{X}\right]\alpha_{ij}\right) + w_j - \delta_{ij}, \forall\ i, j = 1,\ldots,J \quad (3)$$

Where $A = \left(\sum_{l=0}^{L} \beta_{il} (ln\left(X - c'p\right) - w'lnp)^l + \sum_{k=1}^{N} \alpha_{ik} lnp_{kt}\right)$ and δ_{ij} is the Kronecker delta, which is equal to 1 if i=j, and 0 otherwise. The expenditure elasticity is computed as follows:

$$E = (diag\left(W\right))^{-1}$$
$$\left[[I_j + \left(\left(\frac{X - c'p}{X}\right) * B\right)\left(lnp\right)'\right]^{-1}\left[\frac{c * p}{X} + \frac{c'p}{X} A + B\right]\right] + 1_j \quad (4)$$

Where E is the (J x 1) vector of expenditure elasticities with e_i representing ith element, W is the (J x 1) vector of observed energy source budget shares, I_J is an identity matrix, B is a (J x 1) vector with the i^{th} element given by $\sum_{l=1}^{L}\beta_{il} l y^{l-1}$ with $y = (\ln\left(X - c'p\right) - w'lnp)$, lnp is the (J x 1) vector of log prices, A is defined as before, and 1_J is the (J x 1) vector of ones, and c*p stands for Hadamard-Schur product. The uncompensated (Marshallian) prices elasticities (e_{ij}^M) are computed using the Slutsky equation, compensated price elasticity (e_{ij}^H), and expenditure elasticity (e_j) estimates and are given by:

$$e_{ij}^M = e_{ij}^H - e_i w_j \quad (5)$$

Due to the law of demand, it is anticipated that own-price elasticities have a negative value. Also, compensated cross-price elasticities are anticipated to be positive due to energy sources being substitutes for one another. Finally, positive values are expected for expenditure elasticities.

When estimating the GEASI demand model, there are two practical concerns that merit consideration with one being total expenditure endogeneity and the other price endogeneity. The endogeneity of total expenditure is attributed to the simultaneity bias, stemming from total expenditures showing up on both sides of the budget share equations. The endogeneity in prices may arise from their simultaneous determination by demand and supply forces (Zhen et al., 2013). In the current study, neither endogeneity in total expenditure nor in prices is accounted for due to the lack of the information on relevant instruments given the aggregate level of the data used[2]. Thereby, in spirit of Nakamura and Nakamura (1998) and Park and Davis (2001), the rest of the analysis is conducted without accounting for endogeneity issue.

The welfare implications of the projected decrease in the natural gas price by 9% by 2030 in the wake of IRA-related policies are assessed with the Hicksian compensating variation (CV), which shows the amount of income change needed to return a consumer to their original utility level after a price change, in a way that allows them to consume the same level of utility they had before the change (Hausman, 1981). Following (Hausman, 1981), let *E(p, u)* denote the minimum expenditure necessary to get utility level *u* at a given price vector *p*. Also, let p_0, u_0, and p_1 represent initial price vector, utility level, and new price vector, respectively. Then, the CV can be computed as follows:

$$CV = E\,(p_1, u_0) - E\,(p_0, u_0) = p_1\, q^h\,(p_1, u_0) - p_0\, q_0\,(p_0, u_0) \tag{6}$$

Where $q^h\,(p_1, u_0)$ represents the compensated demand, evaluated at a price p_1 and initial utility level of u_0. The following vector of compensated quantity changes helps operationalize equation (6):

$$dq^h = q^h\,(p_1, u_0) - q_0\,(p_0, u_0) \tag{7}$$

Resulting in the following version of the CV:

$$CV = p_1\, dq^h + dpq_0\,(p_0, u_0), \tag{8}$$

Where the vector of price changes $dp=p_1-p_0$ and is computed as follows:

$$\frac{dq^h}{q} = \sum e^H \left(\frac{dp}{p}\right) \tag{9}$$

Where e^H represents the compensated elasticity matrix.

3. DATA

We use monthly time-series data from January of 2009 through December of 2020 for a total of 144 observations concerning price and quantity information on the following major energy sources: Natural gas, coal, nuclear energy, wind, solar, and geothermal energy (the price information on oil/petroleum was unavailable). The monthly consumption of energy sources measured in megawatt hour (MWh) came from the U.S. Energy Information Administration (2023a). For energy prices, we utilize "levelized costs of energy" in \$/MWh borrowed from Lazard Ltd. (2023). Levelized costs of energy is defined as the minimum price that needs to be paid for the power plant to break even over its lifetime (Roser, 2020). To remove the inflationary impact, all the prices are deflated using Consumer Price Index provided by the Federal Reserve Bank of St. Louis (2025).

The summary statistics of quantities, prices, and budget shares of the energy sources are presented in Table 1.

According to the results in Table 1, the mean values for quantities reveal that natural gas is by far the dominant energy source, with an average value of approximately 677 million MWh. This is followed by coal at around 389 million MWh and nuclear at roughly 204 million MWh, indicating these three are the primary contributors to electricity generation. At the same time, renewable sources contribute significantly less, with wind averaging 44 million MWh, solar at 12 million MWh, and geothermal at just over 5 million MWh. The disparity underscores the continued reliance on fossil fuels and nuclear energy for the bulk of electricity production, while renewables, though present, play a relatively minor role in terms of total output.

In terms of average prices, natural gas stands as the most expensive option at approximately \$184.15/MWh, while nuclear and coal are priced lower at \$111.81 and \$97.10/MWh, respectively. Solar and geothermal follow with mean prices of \$95.12 and \$90.96/MWh, respectively, while wind has the lowest average price at \$58.90/MWh.

Budget share data show that natural gas commands the largest mean share of 65.34%, far surpassing any other source. Coal follows with 20.31%, while nuclear accounts for 12.56%, indicating these three sources consume the vast majority of the energy budget. Renewable sources represent a very small fraction of expenditure, with wind at 1.19%, solar at 0.35%, and geothermal at just 0.25%. This distribution reflects a systemic emphasis on traditional energy sources in budget allocations.

4. ESTIMATION RESULTS

The GEASI demand system for six energy sources is estimated with the iterated seemingly unrelated regression approach, using the MODEL procedure in the SAS 9.4 statistical software (SAS 9.4, 2013). During the estimation process, the budget share equation for the geothermal energy is left out to circumvent issues related to the singularity of the variance-covariance matrix of disturbance terms. Nonetheless, the parameters of this budget share equation are retrieved by applying the theoretical constraints of adding-up, homogeneity, and symmetry.

We identify the "best" degree of the real expenditure polynomial function by conducting a series of log-likelihood ratio tests for each degree of the function, which is sequentially increased by one starting from a linear GEASI model. Based on the P-values from the log-likelihood ratio tests (which are equal to zero for up to the

2 We tried to remedy the total expenditure endogeneity with income proxy variables such as real Gross Domestic Product or percentage of people below the poverty level, and price endogeneity with respective producer price indices as instruments, however, the estimation results from these reduced-form equations yielded statistically insignificant parameter estimates with signs inconsistent with theory. As such, following Nakamura and Nakamura (1998) and Park and Davis (2001), due to limited instruments available at the aggregate level of the data, we proceeded without controlling for endogeneity.

Table 1: Summary statistics of quantities, prices, and budget shares of energy sources (n=144)

Variables	Mean	Standard deviation	Minimum	Maximum
Quantities (MWh)				
Natural gas	677,466,061	137,802,699	450,427,082	1,040,415,780
Coal	388,640,604	98,144,251	151,015,126	585,722,463
Nuclear	203,574,016	14,850,716	167,279,985	228,729,075
Wind	44,306,889	17,839,618	13,302,789	85,121,027
Solar	12,060,900	10,071,749	1,136,530	40,613,203
Geothermal	5,097,741	227,759.88	4,094,789	5,508,271
Prices ($/MWh)				
Natural gas	184.1466	34.3456	142.0606	278.4148
Coal	97.0997	7.0860	87.9438	112.3783
Nuclear	111.8072	17.0791	90.1352	138.4546
Wind	58.8973	30.5761	31.4192	145.6735
Solar	95.1234	82.0749	29.2176	363.4579
Geothermal	90.9593	14.5679	60.9906	109.9312
Budget shares (%)				
Natural gas	65.3402	0.0421	0.5748	0.7305
Coal	20.3087	0.0494	0.0985	0.3040
Nuclear	12.5594	0.0321	0.0732	0.1961
Wind	1.1927	0.0027	0.0061	0.0184
Solar	0.3469	0.0017	0.0009	0.0082
Geothermal	0.2521	0.0005	0.0012	0.0035

Researcher (s) own analyses calculated (or derived) based in part on data from U.S. Energy Information Administration (2023a) and Lazard Ltd. (2023)

5th/quintic degree), the 5th degree GEASI model is found to be the superior specification. Therefore, the remainder of the analysis is conducted utilizing the 5th degree GEASI demand model.

Table 2 repots parameter estimates, their standard errors, R^2s, and Durbin-Watson statistics from the GEASI demand model at the 1%, 5%, and 10% significance levels.

The Durbin-Watson statistics together with the statistically significant serial correlation coefficient of ρ imply that the serial correlation is properly addressed in the GEASI demand model. The R^2s range from 26.33% (geothermal) to 96.50 (nuclear), indicating a reasonably good fit for most of the budget share equations. A sporadic statistical significance associated with the seasonal dummy variables indicate the presence of seasonality in the consumption of natural gas, coal, and wind energy.

The pre-committed demand parameter estimate is positive and statistically significant only for geothermal energy.[3] When this parameter estimate is converted into actual MWh consumed, it translates into 4.9 million MWh, which represents about 96.77% of average geothermal energy consumption**.** No evidence of precommitment is found for the rest of the energy sources. The rest of the GEASI demand model parameter estimates are utilized to calculate both compensated (Hicksian) and uncompensated (Marshallian) price elasticities of demand, along with expenditure elasticities, at the sample means for all the energy sources.

Table 3 depicts uncompensated (Marshallian) own-price, cross-price, and expenditure elasticities of demand.

3 A negative parameter estimate on pre-committed demand for nuclear energy implies that as pre-committed (or "non-discretionary") consumption of nuclear energy increases, the share or quantity of discretionary demand for this energy source decreases, however, nothing can be concluded about the actual pre-committed consumption.

The own-price elasticities, located on the main diagonal, are negative and statistically significant for natural gas, coal, and nuclear energy, indicating that demand for each energy source decreases as its price increases, consistent with economic theory. In particular, natural gas, coal, and nuclear energy exhibit an own-price elasticity of −0.7454, −0.1987, and −0.2407 suggesting that a 1% increase in respective prices reduces the quantity demanded by approximately 0.75%, 0.20%, and 0.24% for natural gas, coal, and nuclear energy, respectively, holding other factors constant. Additionally, these own-price elasticity estimates are less than unity in absolute value implying an inelastic demand for natural gas, coal, and nuclear energy. These results compare favorably with those from Rowland et al. (2017) who also found an inelastic demand for coal (−0.868). It needs to be pointed out that the own-price elasticity estimates are negative for wind and geothermal energy, although they are found to be statistically insignificant. Cross-price elasticities, shown off-diagonal, emerge as negative suggesting a complementary relationship between energy sources and indicating that the income effect outweighs the substitution effect. However, the competitive relationship between the energy sources is discussed below in terms of compensated cross-price elasticities which are net of income effect and reflect only substitution effect. Negative uncompensated cross-price elasticities for natural gas and coal were also reported by Rowland et al. (2017) and for natural gas and solar by Bakhtavoryan et al. (2025).

Expenditure elasticities are positive and statistically significant across all energy sources, with natural gas (1.1247) and geothermal energy (1.1007) showing strong responsiveness to changes in total energy expenditure. These values indicate that these energy sources are expenditure elastic, meaning their demand increases more than proportionally as total energy spending rises. At the same time, nuclear energy (0.4610) emerges as the most expenditure inelastic energy source. Our results for expenditure elastic natural gas aligns with findings from.

Table 2: Parameter estimates, standard errors, goodness-of-fit (R^2), and Durbin-Watson statistics from the GEASI demand model

Parameters	Natural gas	Coal	Nuclear	Wind	Solar	Geothermal
Pre-commitments (t_{i0})	−0.0067	−0.0128	−0.1025***	−0.0009	0.0005	0.0004***
	(0.0135)	(0.0104)	(0.0105)	(0.0011)	(0.0003)	(0.0001)
Quarter 1	−0.0080	0.0022	0.0015	0.0002	−0.0001	1.963E−6
	(0.0079)	(0.0032)	(0.0014)	(0.0005)	(0.0001)	(0.00003)
Quarter 2	0.0090	−0.0127***	0.0017	0.0009*	−0.0002	−0.0001
	(0.0105)	(0.0049)	(0.0022)	(0.0005)	(0.0001)	(0.00004)
Quarter 3	0.0238***	−0.0016	0.0017	0.0001	−0.0002	−0.00003
	(0.0083)	(0.0041)	(0.0015)	(0.0004)	(0.0001)	(0.00003)
Price (α_{1j}) Natural gas	0.0218*	0.0228**	−0.0417***	−0.0040	0.0010	0.0001
	(0.0114)	(0.0107)	(0.0043)	(0.0028)	(0.0011)	(0.0003)
Price (α_{2j}) Coal		0.0017	−0.0248***	0.0005	−0.0002	−0.00002
		(0.0099)	(0.0029)	(0.0010)	(0.0003)	(0.0001)
Price (α_{3j}) Nuclear			0.0664***	−0.0004	0.0007***	−0.0002***
			(0.0056)	(0.0005)	(0.0001)	(0.00003)
Price (α_{4j}) Wind				0.0029	0.0009	0.00003
				(0.0030)	(0.0008)	(0.0002)
Price (α_{5j}) Solar					−0.0024*	−0.0001
					(0.0012)	(0.0002)
Price (α_{6j}) Geothermal						0.0001
						(0.0001)
Real income (β_{i0})	0.6657***	0.2081***	0.1085***	0.0118***	0.0033***	0.0026***
	(0.0065)	(0.0053)	(0.0033)	(0.0005)	(0.0001)	(0.00004)
Real income (β_{i1})	0.0815***	−0.0111	−0.0677***	−0.0024***	−0.0005***	0.0003**
	(0.0136)	(0.0146)	(0.0073)	(0.0007)	(0.0002)	(0.0001)
Real income (β_{i2})	−0.0004	0.0016	−0.0014	0.0002	−0.0001	0.0001
	(0.0075)	(0.0063)	(0.0023)	(0.0006)	(0.0002)	(0.00004)
Real income (β_{i3})	−0.0051	0.0014	0.0032	0.0006	−0.0001	0.00002
	(0.0091)	(0.0075)	(0.0029)	(0.0007)	(0.0002)	(0.0001)
Real income (β_{i4})	−0.0019	0.0008	0.0013	−0.0002	0.00003	−3.11E−6
	(0.0036)	(0.0030)	(0.0011)	(0.0003)	(0.0001)	(0.00002)
Real income (β_{i5})	0.0014	−0.0002	−0.0013	0.0001	0.00002	−6.73E−6
	(0.0030)	(0.0025)	(0.0010)	(0.0002)	(0.0001)	(0.00002)
R-squared (%)	78.24	89.24	96.50	67.26	93.10	26.33
Durbin Watson	0.7704	0.6950	1.7446	1.8754	1.1479	0.9695
ρ	0.7002***					
	(0.0299)					

The standard errors are in parentheses. ***, **, * identify parameter estimates that are statistically different from 0.00 at the 0.01, 0.05, and 0.10 significance levels, respectively. Researcher (s) own analyses calculated (or derived) based in part on data from U.S. Energy Information Administration (2023a) and Lazard Ltd. (2023)

Table 3: Uncompensated (Marshallian) price and expenditure elasticity estimates from the GEASI demand model

Energy sources	Natural gas	Coal	Nuclear	Wind	Solar	Geothermal	Expenditure
Natural gas	−0.7454***	−0.2201***	−0.1452***	−0.0135***	−0.0039***	−0.0028***	1.1247***
	(0.0049)	(0.0045)	(0.00001)	(1.664E−6)	(0.00001)	(1.804E−6)	(0.0034)
Coal	−0.5319***	−0.1987***	−0.1192***	−0.0112***	−0.0033***	−0.0024***	0.9453***
	(0.0463)	(0.0380)	(0.0017)	(0.00008)	(2.522E−6)	(8.398E−7)	(0.0971)
Nuclear	−0.4079***	−0.0947***	−0.2407***	−0.0055***	−0.0016***	−0.0012***	0.4610***
	(0.0004)	(0.0045)	(0.0082)	(0.00002)	(0.000016)	(1.269E−8)	(0.0674)
Wind	−0.6275***	−0.1516***	−0.1029***	−0.1923	0.0033	−0.0020***	0.7971***
	(0.0050)	(0.0231)	(0.0026)	(0.1234)	(0.0098)	(0.0001)	(0.0013)
Solar	−0.2805	−0.1841***	−0.0467**	0.0608	1.1425	−0.0015	0.87028***
	(0.3972)	(0.0086)	(0.0204)	(0.1158)	(0.8467)	(0.0035)	(0.0039)
Geothermal	−0.6813***	−0.2250***	−0.1422***	−0.0129***	−0.0025	−0.0467	1.1007***
	(0.0805)	(0.0055)	(0.00003)	(0.0021)	(0.0066)	(0.0483)	(0.0087)

Elasticities are evaluated at the sample mean values. Standard errors are provided in the parentheses. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level, respectively. Researcher (s) own analyses calculated (or derived) based in part on data from U.S. Energy Information Administration (2023a) and Lazard Ltd. (2023)

Rowland et al. (2017) and Bakhtavoryan et al. (2025) who reported expenditure elasticity for natural gas to be 1.85 and 1.3652, respectively. Also, similar to our findings, Rowland et al. (2017) reported expenditure elasticity for coal to be 0.988, and Bakhtavoryan et al. (2025) found solar energy to be expenditure inelastic (0.6812).

Table 4 depicts the compensated or Hicksian price elasticity estimates from the GEASI demand model, which isolate substitution effects by holding utility constant.

The own-price elasticities along the main diagonal are all negative and statistically significant, as expected. Notably, solar power

Table 4: Compensated (Hicksian) price elasticity estimates from the GEASI demand model

Energy sources	Natural gas	Coal	Nuclear	Wind	Solar	Geothermal
Natural gas	−0.3132***	0.2379***	0.0617***	0.0058	0.0051***	0.0041**
	(0.0175)	(0.0164)	(0.0065)	(0.0042)	(0.0017)	(0.0017)
Coal	0.7655***	−0.7884***	0.0034	0.0144***	0.0027*	0.0024***
	(0.0528)	(0.0487)	(0.0143)	(0.0047)	(0.0014)	(0.0004)
Nuclear	0.3211***	0.0055	−0.3459***	0.0092**	0.0089***	0.0012***
	(0.0338)	(0.0232)	(0.0448)	(0.0036)	(0.0011)	(0.0002)
Wind	0.3159	0.2450***	0.0965**	−0.7415***	0.0794	0.0047
	(0.2321)	(0.0805)	(0.0384)	(0.2494)	(0.0631)	(0.0134)
Solar	0.9551***	0.1555*	0.3208***	0.2729	−1.6789***	−0.0255
	(0.3160)	(0.0801)	(0.0395)	(0.2169)	(0.3586)	(0.0652)
Geothermal	0.7070***	0.1958***	0.0613***	0.0222	−0.0351	−0.9513***
	(0.1058)	(0.0289)	(0.0108)	(0.0636)	(0.0897)	(0.0534)

Elasticities are evaluated at the sample mean values. Standard errors are provided in the parentheses. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level, respectively. Researcher (s) own analyses calculated (or derived) based in part on data from U.S. Energy Information Administration (2023a) and Lazard Ltd. (2023)

(−1.6789) exhibits large own-price elasticity (elastic demand), indicating high price sensitivity in demand after adjusting for income effects. In contrast, there is an inelastic demand for energy sources like natural gas (−0.3132), coal (−0.7884), nuclear energy (−0.3459), wind (−0.7415), and geothermal energy (−0.9513). Elastic demand for solar energy was confirmed by Bakhtavoryan et al. (2025), while inelastic demand for natural gas was confirmed by Bakhtavoryan et al. (2025) and Rowland et al. (2017). Finally, our finding of inelastic demand for coal compares favorably with that from Rowland et al. (2017).

Most of the off-diagonal cross-price elasticities are positive and statistically significant, consistent with net substitutability between energy sources. The strongest statistically significant substitutability relationship is observed between solar energy and natural gas (0.9551) and the weakest substitutability relationship is found between nuclear and geothermal energy (0.0012). Our finding of net substitutability between energy sources is consistent with that from Rowland et al. (2017) involving natural gas and coal, and with Bakhtavoryan et al. (2025) involving natural gas and solar energy.

As a final exercise, we assess the effects of natural gas price decrease on consumer welfare with the Hicksian compensating variation (CV) measure. In particular, using equation (8) above, a 9% decrease in the natural gas price by 2030, as forecasted by the U.S. Energy Information Administration because of lower U.S. demand propelled by IRA-related policies and investments (U.S. Energy Information Administration, 2023b), yields the value of CV equal to $335,684,072.

5. CONCLUSION, IMPLICATIONS, AND RECOMMENDATIONS FOR FUTURE RESEARCH

We estimate a GEASI demand model to analyze the demand for energy sources such as natural gas, coal, nuclear, wind, solar, and geothermal energy, using monthly time-series data from January of 2009 through December of 2020. The use of the GEASI demand model permits the imposition of flexible Engel curves and allows for unobserved heterogeneity.

The emergence of the 5$^{\text{th}\circ}$ (quintic) GEASI demand model as the best specification comes to empirically prove that the use of demand systems with linear real expenditures is not the most viable option when studying the demand for energy sources. As for the other findings, according to the computed uncompensated own-price elasticities, the demand for natural gas, coal, and nuclear energy emerges as inelastic. The implication of this empirical finding is that the manufacturers of natural gas, coal, and nuclear energy need to consider an increase in price in order to maximize the short-run total revenue from the sales. Also, inelastic demand has implications for government taxation policy or producer pricing strategies in that they may increase prices without losing significant demand, at least in the short run.

Per positive values of expenditure elasticities, the quantity demanded of all energy sources is anticipated to go up to the extent that expenditures on them increase, with proportionally lower increase for coal, nuclear energy, wind, and solar energy, and with proportionally larger increase for natural gas and geothermal energy.

According to the compensated cross-price elasticity estimates, the energy sources emerge as substitutes competing against each other. This information is of importance to energy source manufacturers in their decision regarding input procurement and inventory management given the changes in the prices of competing energy sources. This finding also reinforces the idea that price-based policies (carbon taxes or removal of fossil fuel subsidies) can shift demand toward cleaner energy sources.

Importantly, the computed pre-committed demand comprises about 97% of average geothermal energy consumption meaning that a large portion of geothermal energy consumption is not responsive to price or income changes. The direct implication of this is that price-based instruments (like taxes or subsidies) are less effective at changing demand for it, and policy should focus on long-term capacity planning (assuming the objective is the expansion of geothermal energy).

The empirical finding that a 9% decrease in the natural gas price by 2030, driven by declining U.S. demand due to Inflation Reduction Act (IRA)-related policies and investments, results in a CV of $335.7 million has economic and policy implications. In particular, this outcome highlights the dual benefit of clean energy policy: reduced fossil fuel reliance and measurable consumer welfare improvements.

A few possible extensions for future research need to be mentioned. First, it is recommended that future research be carried out at a more disaggregate level (household or city). Second, remedying the endogeneity in total expenditure as well as energy prices by incorporating data on energy supply determinants could enhance the accuracy and reliability of the estimated energy demand structure. Third, if possible, future research should include oil, hydroelectric power, and biomass energy price and quantity into analysis as additional energy sources. Nonetheless, irrespective of these recommendations, the current study contributes significantly to the extant literature dealing with the demand for energy sources facilitating educated decision-making for industry stakeholders and policymakers in their pursuit of energy security.

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