Precautionary Electrification*

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Abstract

This paper argues that households engage in precautionary electrification, i.e. they adopt electricity instead of gas to insure themselves against volatile gas prices. The analysis is motivated by two facts: (1) natural gas prices in the United States have been fluctuating more than electricity prices over the past two decades; and (2) lower-income households are more likely to rely on electricity for heating than higher-income households. Using state-level data from 1999 to 2023, I show that greater gas price volatility leads to higher electrification, particularly among low-income households. I calibrate a structural model of household energy choice with non-homothetic preferences and costly fuel switching which matches the empirical relationship between income, fuel choice, and energy expenditure. In the model, higher gas volatility increases electrification. However, it also decreases welfare, with poorer households suffering the most. Finally, I compare two insurance schemes (flat transfer and proportional subsidy) and show that precautionary electrification creates a policy trade-off between short-term insurance and long-term electrification.

Keywords: electrification, energy price, households energy choice, risk.
JEL codes: D12, D81, E21, Q41, Q48.

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1 Introduction

Volatile energy prices have become a defining feature of the global economy. The COVID-19 pandemic and Russia's 2021 invasion of Ukraine exposed households and policymakers to sharp, unpredictable swings in energy costs. At the same time, structural shifts such as the shale revolution and the globalization of natural gas markets have sustained high volatility in gas prices, in contrast with the relative stability of electricity prices in the United States. These developments raise a central question: how do households adjust their energy choices in response to differences in the volatility of energy prices?

This paper documents and quantifies a new channel, precautionary electrification, through which households respond to gas price risk by shifting toward electricity. In environments where gas prices are more volatile than electricity prices, households adopt electricity as a form of self-insurance against energy price fluctuations. The strength of this mechanism declines with income: poorer households, who devote a larger share of expenditure to energy and are therefore more exposed to gas price risk, exhibit stronger precautionary incentives to electrify. As a result, energy price volatility shapes both the composition of household energy demand and the distributional exposure to energy shocks.

Two motivating facts guide the analysis. First, over the past two decades, the residential prices for natural gas have been substantially more volatile than for residential electricity prices (Apergis, Bowden, and Payne, 2015, Regnier, 2007, Chan and Grant, 2016, Wiggins and Etienne, 2017). Between 1999 and 2023, the coefficient of variation of U.S. gas prices ranged between 9% and 18%, compared with 3% to 6% for electricity. Second, household fuel choice is strongly correlated with income. Using PSID panel data, I show that a 1% increase in income is associated with a 9 percentage point lower probability of using electricity as the primary heating source. This relationship holds after controlling for local climate conditions and demographics, and extends to homeowners. Together, these facts suggest a link between income heterogeneity, fuel choice, and exposure to energy price risk.

I provide direct evidence for precautionary electrification by combining state-level residential energy price data to construct an annual measure of relative gas volatility, defined as the ratio of gas price volatility to electricity price volatility. Exploiting cross-state variation in this measure, I show that higher gas price risk is associated with greater electrification: a 1% increase in relative gas volatility raises the electrification rate by 0.06 percentage points. The effect is strongest among low-income households, consistent with a precautionary motive rather than a purely technological or preference-driven shift.

To interpret these findings, I develop a structural model of household energy choice in which households select both the energy type (gas or electricity) and consumption level under non-homothetic preferences. Gas prices follow a stochastic process with exogenous shocks, while electricity prices are constant. Switching fuels entails financial and utility costs.

In this environment, poorer households, who allocate a larger share of expenditure to energy, face greater welfare losses from gas volatility and therefore exhibit stronger incentives to electrify. Calibrating the model to U.S. data reproduces key empirical patterns: the positive relationship between income and energy consumption, the declining energy budget share with income, and the income gradient in fuel choice.

I use a counterfactual to quantify the welfare and distributional implications of energy price volatility. A 10% increase in gas price volatility raises aggregate electrification rates by 1.7 percentage points and disproportionately drives electrification among households in the bottom income quintile. Welfare losses from gas volatility are almost twice as large for the poorest households as for the richest, highlighting the regressive nature of energy price risk.

Finally, I examine the policy implications of precautionary electrification. Because volatility itself induces long-term shifts in energy technology adoption, policies that insure households against energy price risk may dampen incentives to electrify. I compare two policy designs commonly implemented during the 2021–22 European energy crisis: a flat transfer and a proportional energy-bill subsidy, holding total fiscal cost constant. Both raise short-term welfare but reduce electrification. The flat transfer delivers greater welfare gains, especially for poorer households, while the proportional subsidy better preserves electrification incentives. The optimal policy therefore depends on whether policymakers prioritize short-term insurance or long-term electrification.

Related literature. This paper relates to four strands of the literature: the effects of energy price shocks; the role of uncertainty in household decision-making; household fuel choice; and energy macroeconomics.

A large literature studies the effects of energy price changes on households and the macroeconomy. Within this literature, one line of research estimates households' price elasticities of energy demand (e.g., Alberini, Gans, and Velez-Lopez, 2011, Alberini and Filippini, 2011, Alberini, Khymych, and Šcasnỳ, 2019, Miller and Alberini, 2016, Gelman et al., 2023). Another line studies the aggregate effects of energy price shocks (e.g. Pindyck and Rotemberg, 1983, Sweeney, 1984), often exploiting the exogeneity of oil shocks (e.g. Kilian, 2008, Kilian and Lewis, 2011, Edelstein and Kilian, 2009, Kilian, 2014, Kilian and Vigfusson, 2011, Gagliardone and Gertler, 2023). More recently, work has examined the heterogeneous distributional effects of energy price shocks across households (e.g. Känzig, 2023; Auclert et al., 2023; Bobasu, Dobrew, and Repele, 2025; Aguilar and Fuentes-Albero, 2025). I contribute to this literature by focusing not on the level of prices but on their volatility, and by distinguishing between electricity and gas consumption, thereby uncovering an important channel of heterogeneity in exposure to shocks.

This paper is also related to work on how aggregate uncertainty affects household behavior. Coibion et al. (2024) show that higher macroeconomic unertainty reduces household spending on nondurables, while Kumar, Gorodnichenko, and Coibion (2023) study the effects of uncertainty on firms' decisions. Alberini, Ščasnỳ, et al. (2023) provide direct evidence that households form expectations about energy prices and that they are especially uncertain about electricity and gas prices. In Europe, Cevik and Zhao (2025) measure the spillovers from electricity price volatility across countries. My contribution is to show that households' expectations about energy price volatility influence not only their consumption level but also their fuel choice, with long-run implications for the composition of residential energy demand.

A third strand examines the determinants of household' adoption of different fuels. Davis (2011) and Davis (2025) study the role of energy prices in households' adoption of electricity; Rapson and Bushnell (2024) analyze the diffusion of electric vehicles; and Allcott, Kwon, and Snyder (2024) highlight distributional aspects of electrification. I extent this literature by emphasizing volatility rather than levels of energy prices as a determinant of fuel choice. In my framework, households anticipate that gas prices are more volatile than electricity prices, and poorer households – who devote a larger share of expenditures to energy – are more likely to switch to electricity in response to that risk.

Finally, this paper contributes to the growing literature macroeconomics, energy and climate policy. Foundational work in this area began with Integrated Assessment Models (Nordhaus, 1993), and subsequent contributions have studied optimal carbon taxes (Golosov et al., 2014), fiscal instruments for mitigation (Barrage, 2020) and climate policy uncertainty (Fried, Novan, and Peterman, 2021). More recent research embeds energy into heterogeneous-agent models, building on Aiyagari (1994). Examples include Fried (2024) on temperature shocks, Känzig (2023) on the distributional effects of carbon pricing, and Krusell and Smith Jr (2022) on IAMs with heterogeneous agents. My paper adds to this literature by modeling energy consumption along both the extensive (fuel type) and intensive (quantity) margins, incorporating non-homothetic preferences that generate heterogeneous exposure to energy price volatility. The results suggest that volatility itself may be an underexplored channel accelerating residential electrification.

Roadmap. The remainder of the paper proceeds as follows. Section 2 presents the empirical motivation and evidence for precautionary electrification using data from the PSID. Section

3 develops and calibrates a structural model of household energy choice that reproduces the empirical patterns. Section 4 uses the model to evaluate the effects of insurance policies on electrification and welfare in the presence of precautionary motives. Section 5 concludes and outlines directions for future research.

2 Motivating Facts

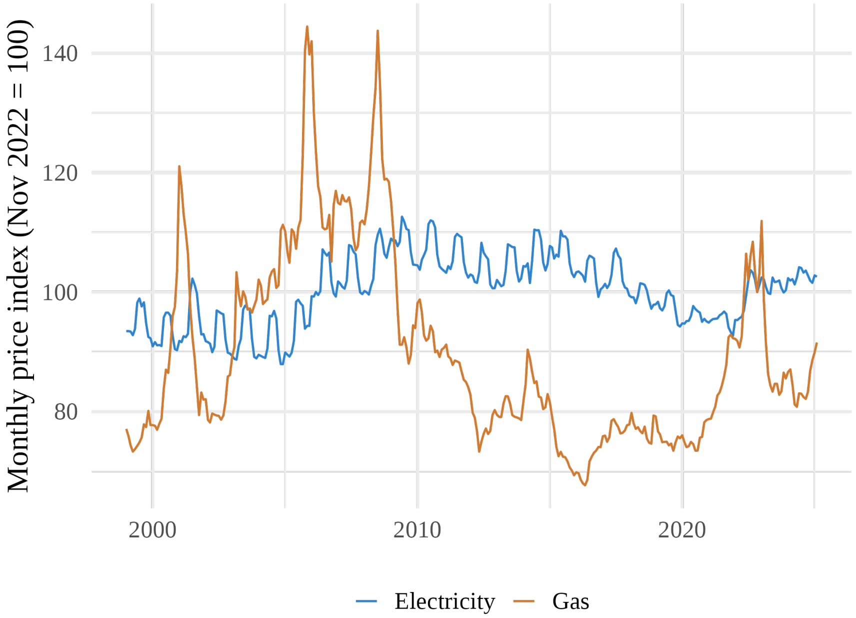
This section presents the empirical motivation for the analysis. I document two key facts about U.S. household energy use and provide direct evidence consistent with a precautionary electrification mechanism. First, residential gas prices have been substantially more volatile than electricity prices over the past 25 years. Second, households differ systematically in their choice of energy source: higher-income households rely disproportionately on natural gas, while lower-income households depend more heavily on electricity. Together, these facts imply that income groups face systematically different exposure to energy price risk. I then show suggestive evidence that higher gas price volatility is associated with greater household electrification, consistent with the idea that households adopt electricity as a precaution against gas price uncertainty.

2.1 The relative volatility of residential gas prices

Figure 1 plots monthly U.S. residential price indices for electricity and natural gas from January 1999 to February 2025, deflated to November 2022 dollars using the CPI. To make volatility more visible, I present the raw series without de-seasonalization, so that both seasonal fluctuations and longer-term swings are apparent. The contrast between the two series is striking: residential gas prices are considerably more volatile than electricity prices, a pattern that holds throughout the sample period.

Several distinct periods can be identified in the gas series. Between 1999 and 2009, volatility

Figure 1: Monthly US residential electricity and gas price indices, 1999–2025



Notes: Monthly price indices are based on U.S. residential retail prices for electricity and natural gas. Prices are deflated to November 2022 dollars using the CPI (all items) and normalized to 100 in November 2022. The figure illustrates the greater volatility of gas prices relative to electricity over the past quarter century, reflecting differences in storage, regulation, and exposure to global energy shocks.

was extremely high, with a coefficient of variation of 18%.[1] From 2009 until the eve of the COVID-19 pandemic, volatility fell markedly, with the coefficient of variation dropping to 8.8%. Since 2021, volatility has risen again to 9.3%, during a period shaped by the global energy crisis following Russia's invasion of Ukraine. The existence of such shifts in volatility is consistent with the findings of Hailemariam and Smyth (2019), who estimate a structural VAR with stochastic volatility and identify significant regime breaks in gas price uncertainty, closely matching the patterns visible in the raw data.

Electricity prices, in contrast, have remained remarkably smooth. While they display predictable seasonal patterns, the overall level of volatility has been consistently low: the coefficient of variation of monthly electricity prices was 6.3% between 1999 and 2009, fell to 4.4%

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[1] The coefficient of variation is defined as the standard deviation divided by the mean, which allows comparison of relative volatility across periods with different average price levels.

between 2009 and 2021, and declined further to 3.3% since 2021. In other words, if anything, electricity prices have become less volatile over time, in sharp contrast to the fluctuations observed in gas.

Why is gas so much more volatile than electricity? The key lies in how the two markets are organized. Natural gas prices are determined in wholesale commodity markets, increasingly integrated with international trade since the early 2000s, when gas markets were deregulated (Apergis, Bowden, and Payne, 2015, Wiggins and Etienne, 2017, Hailemariam and Smyth, 2019). As a result, they are highly sensitive to exogenous supply shocks: the shale gas boom in the late 1990s and early 2000s generated large downward swings in prices, while more recently, geopolitical disruptions such as the war in Ukraine triggered large spikes. Because gas is traded internationally and storage is costly, short-run shocks to supply or transportation constraints translate quickly into end-use prices.

Electricity, by contrast, is consumed locally and delivered through highly regulated utilities (U.S. Energy Information Administration, 2023). Even though natural gas is a key input into electricity generation, residential electricity tariffs are buffered from wholesale price volatility by regulation, long-term contracts, cross-subsidization, and the mix of other generation sources (coal, nuclear, renewables). In effect, the institutional and technological structure of the electricity sector absorbs much of the volatility present in the underlying gas market. This explains why households face far more stable electricity prices even when natural gas, upstream, is subject to dramatic swings.

Taken together, the evidence highlights a robust stylized fact: U.S. residential gas prices are volatile, subject to sharp regime shifts driven by exogenous supply shocks, whereas electricity prices are comparatively smooth, reflecting both regulation and diversified production. This asymmetry provides the central motivation for the model: when households choose between gas and electricity, they face not only different price levels, but fundamentally different degrees of price risk.

2.2 Household income and energy choice

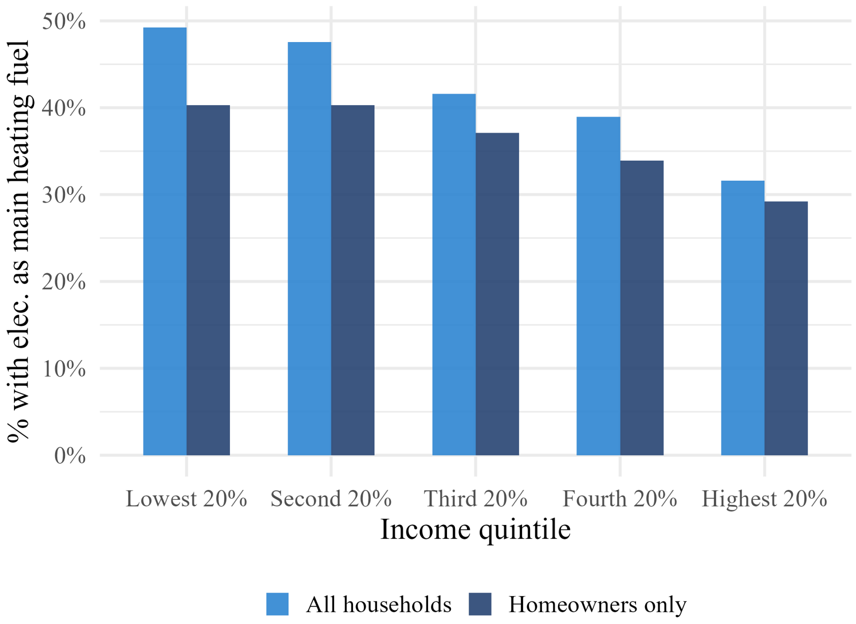
A second key motivating fact is that households are heterogeneous in the type of energy they use. Poorer households relying disproportionately on electricity, while richer households depend more on natural gas. This pattern matters because, as shown above, gas prices are substantially more volatile than electricity prices. Heterogeneity in energy adoption therefore translates directly into heterogeneity in exposure to price risk.

Data. I document these patterns using the Panel Study of Income Dynamics (PSID), a nationally representative longitudinal survey collected biennially since 1968. I focus on waves from 1999 to 2023, when data on households' main heating fuel and energy expenditures are consistently available. The PSID provides rich information on household characteristics, including demographics, housing attributes, and detailed expenditures. Most relevant for this study, the survey records the household's primary heating fuel and annual expenditures on electricity and natural gas.

To account for climatic variation, I merge restricted-use PSID geocodes with daily temperature data from the National Oceanic and Atmospheric Administration (NOAA) and construct annual heating and cooling degree days at the census-tract level (base 65°F/18°C). I restrict the sample to households that use either natural gas or electricity as their primary heating fuel, which together represent about 90 percent of all observations. Following standard PSID conventions, I exclude immigrant refresher samples and drop implausible cases with annual energy expenditures below \$0 or above \$40,000 (2022 USD) or total expenditures below \$2,000. I also remove households missing key housing characteristics or for which temperature data cannot be matched. The final dataset comprises roughly 35,000 household-year observations for 9,598 unique households, or about 3,500 per year. All monetary values are expressed in 2022 dollars using the CPI (all items), and longitudinal survey weights are applied throughout.

Descriptive patterns. Figure 2 plots the share of households that report electricity as their main heating fuel between 2019 and 2023, by income quintile. The light blue bars correspond to the full sample and the dark blue bars to homeowners only. Income quintiles are computed from four-year average income. The relationship is clearly downward sloping: poorer households are more likely to heat with electricity, while richer households predominantly use gas. Among all households, 50% of those in the bottom income quintile heat with electricity, compared with only 30% in the top quintile. The pattern is nearly identical among homeowners, indicating that it is not driven solely by differences in tenure or housing quality.

Figure 2: Share of households with electricity, by income quintile



Notes: The figure plots the average share of U.S. households using electricity as their main heating fuel, by income quintile, over 2019–2023. Data come from the restricted-use PSID geocoded sample. The analysis excludes immigrant refresher samples and households with implausible or missing expenditure data. Estimates are weighted using longitudinal survey weights. Income is measured in real 2022 dollars and computed as the household's four-year average to smooth transitory fluctuations.

Regression evidence. To quantify the income gradient in energy adoption, I estimate a linear probability model of electricity use:

$$\text{hasElectricity}_{ist} = \beta_0 + \beta_1 \log(\text{income}_{it}) + X_{it} + \gamma_t + \gamma_s + \varepsilon_{ist},$$

where $\text{hasElectricity}_{ist}$ indicates whether household i in state s and year t relies on electricity as its main heating fuel. Income is measured as four-year average household income, X_{it} includes controls for climate (heating and cooling degree days), housing characteristics, homeownership status, family size, and the family head's age. I also include year and state fixed effects (γ_t, γ_s) to absorb time and region-specific factors, including permanent differences in energy prices. I estimate the model both for the full sample and for homeowners only.

Table 1 reports the results across three specifications, shown separately for all households (left panel) and for homeowners only (right panel). Columns (1) and (4) present unadjusted estimates, columns (2) and (5) add household-level covariates, and columns (3) and (6) include both covariates and year and state fixed effects. In every specification, the coefficient on log(income) is negative and statistically significant, indicating that higher-income households are less likely to rely on electricity as their main heating fuel. In the fully saturated model with controls and fixed effects, a 1% increase in income is associated with a 0.09-p.p. lower probability of using electricity, confirming a strong and robust income gradient in energy choice.

This results implies that energy choices are strongly stratified by income. Poorer households are disproportionately reliant on electricity, while richer households are more likely to adopt gas. Combined with the fact that energy expenditures decline as a share of income while gas prices are more volatile, this heterogeneity implies that energy price shocks have unequal effects across the income distribution. Poor households, by relying on the less volatile energy source, effectively insure themselves against risk; richer households, by consuming more gas,

Table 1: Income and Electricity adoption

	All households			**Homeowners only**		
	(1) Baseline	(2) + controls	(3) + year/state FE	(4) Baseline	(5) + controls	(6) + year/state FE
log income	-0.29^{***}	-0.15^{***}	-0.10^{***}	-0.20^{***}	-0.13^{***}	-0.09^{***}
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)
Observations	35,780	24,992	24,973	26,835	18,853	18,837
R^2	0.01	0.13	0.23	0.004	0.12	0.24

Notes: Coefficients are from logit regressions. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is a binary indicator for electricity as main heating fuel. Controls include heating and cooling degree-days (base 65°F/18°C), age (squared), house tenure, family size (squared) and house type.

are more directly exposed to volatility. This income–energy link is central to the quantitative model that follows, where households choose both how much energy to consume and which energy source to adopt in the presence of gas price uncertainty.

2.3 Suggestive evidence of precautionary electrification

The two facts above suggest that volatile gas prices and energy choice may be related. In this section, I provide direct evidence consistent with this mechanism by exploiting cross-state variation in the relative volatility of gas and electricity prices.

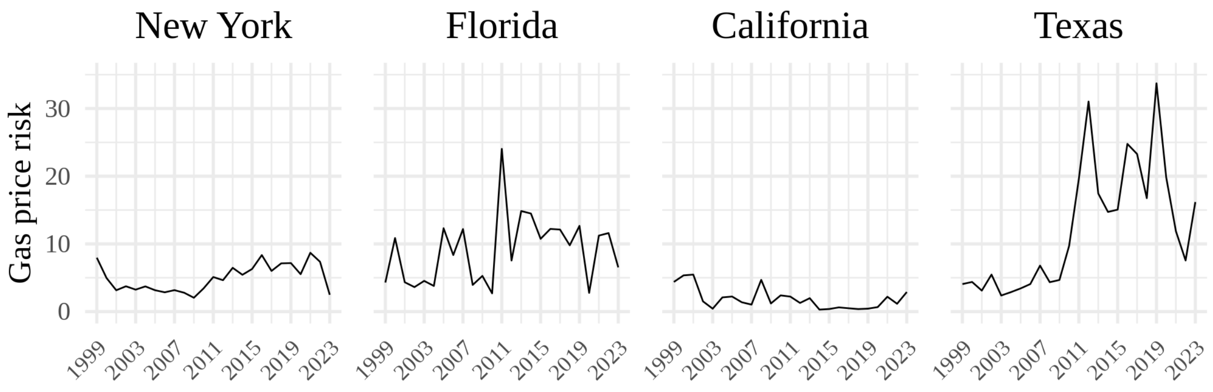
Data. I collect monthly state-level residential electricity and natural gas prices for all U.S. states from 1998 to 2023 and deflate them to November 2022 dollars using the monthly CPI from FRED. For each state s and year t, I construct a measure of relative gas volatility as

$$\widetilde{\sigma}_{st} = \frac{\sigma_{gst}}{\sigma_{\ell st}}, \tag{1}$$

where σ_{gst} is the standard deviation of the log price of gas and $\sigma_{\ell st}$ is the standard deviation of the log price of electricity. A higher value of $\widetilde{\sigma}_{st}$ indicates that gas prices were more volatile relative to electricity prices in that state-year. I interpret this measure as a proxy for relative gas price risk faced by households.

The measure exhibits substantial cross-state and time variation, reflecting differences in energy mix, regulation, and storage capacity. Figure 3 illustrates this heterogeneity for four large states—New York, Florida, California, and Texas, showing distinct trajectories in relative gas volatility across the sample period.

Figure 3: Relative gas price volatility in selected states



Notes: The figure plots the relative volatility of residential gas prices compared to electricity for four large U.S. states, New York, Florida, California, and Texas, over 1999–2023. Relative volatility is defined as the ratio of the standard deviation of monthly log gas prices to that of electricity prices within each year. Prices are deflated to November 2022 dollars using the CPI (all items). The data come from the U.S. Energy Information Administration (EIA). Differences across states reflect variation in fuel mix, regulation, and storage capacity.

Estimation strategy. I test whether higher gas price volatility is associated with greater household electrification and whether this relationship depends on income. To this end, I estimate the following model:

$$\text{Electricity}_{ist} = \beta_0 + \beta_1 \left[\widetilde{\sigma}_{st-1} \times \log(\text{income}_{it})\right] + X_{it} + \gamma_t + \gamma_s + \varepsilon_{ist}, \tag{2}$$

where Electricity_{ist} is an indicator equal to one if household i in state s and year t uses electricity as its main heating fuel. The variable $\widetilde{\sigma}_{st-1}$ is the lagged measure of relative gas volatility, and $\log(\text{income}_{it})$ is four-year average household income. The vector X_{it} includes controls for the lagged relative price of gas to electricity, heating and cooling degree days, housing type, tenure, demographics, and location. Year and state fixed effects, γ_t and γ_s, capture aggregate and region-specific shocks. I use lagged volatility and price ratios to mitigate reverse causality concerns whereby household fuel choices might affect contemporaneous price volatility. The model is estimated separately for the full sample and for homeowners only.

Results. Table 2 summarizes the results. Columns (1)–(3) present estimates for all households, and columns (4)–(6) restrict the sample to homeowners. Within each group, the first specification is unadjusted, the second includes covariates, and the third adds year and state fixed effects.

Table 2: Effect of relative gas volatility on electricity adoption

	All households			**Homeowners only**		
	(1) Baseline	(2) + Controls	(3) + Year/State FE	(4) Baseline	(5) + Controls	(6) + Year/State FE
$\widetilde{\sigma}_{st-1}$	0.09^{***}	0.10^{***}	0.06^{***}	0.06^{***}	0.07^{***}	0.04^{***}
	(0.005)	(0.008)	(0.008)	(0.007)	(0.009)	(0.010)
$\widetilde{\sigma}_{st-1} \times \log(\text{income}_{it})$	-0.004	-0.005^{*}	-0.006^{***}	-0.001	-0.002^{*}	-0.004^{***}
	(0.000)	(0.001)	(0.001)	(0.003)	(0.004)	(0.005)
Observations	35,780	24,992	24,973	26,835	18,853	18,837
R^2	0.09	0.17	0.23	0.11	0.16	0.24

Notes: The dependent variable is an indicator equal to one if household i in state s and year t uses electricity as its main heating source. The key explanatory variable $\widetilde{\sigma}_{st-1}$ measures the relative volatility of residential gas prices to electricity prices in the previous year, computed from monthly EIA data. Specifications progressively add household-level controls (income, tenure, housing type, household size, and age of head) and state and year fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The results provide evidence consistent with a precautionary electrification mechanism. Across all specifications, the coefficient on relative gas volatility is positive and statistically significant: higher gas price risk is associated with a greater probability of using electricity for heating. In the fully saturated model with controls and fixed effects, a one-percent increase in relative gas volatility raises the probability of heating with electricity by approximately 0.06 percentage points.

The interaction term between relative gas volatility and income is negative and statistically significant, indicating that the electrification response to gas price risk is stronger among lower-income households. In other words, households with fewer resources are more likely to shift toward electricity when faced with higher gas price volatility. These findings provide direct evidence of a precautionary electrification motive and suggest that energy price risk contributes to income-based differences in household energy adoption.

I now turn to the structural model, which formalizes this mechanism and quantifies its welfare and policy implications.

3 Model

In this section, I first introduce the quantitative model used to study how volatility in gas prices affects households' energy adoption and consumption decisions. The model is a households decision problem with incomplete markets, idiosyncratic income risk, and an extensive margin of energy choice between gas and electricity. Preferences are non-homothetic and the price of electricity is constant, while the price of gas is volatile. I then show the model implications for households' behavior, the calibration, and the model fit. Finally, I show that the model generates precautionary electrification.

3.1 Environment

Time is discrete and infinite. A unit mass of infinitely lived households faces idiosyncratic income risk and chooses consumption, savings, and an energy technology. Households differ in income and face stochastic energy prices for natural gas, while electricity prices remain stable.

Idiosyncratic income. Each household receives a stochastic endowment z, which follows an AR(1) process:

$$\log z' = \rho_z \log z + \sigma_z \varepsilon_z', \qquad \varepsilon_z' \sim \mathbb{N}(0,1), \tag{3}$$

where ρ_z governs persistence and σ_z the volatility of income shocks.

Energy technologies. Households consume two goods: a non-energy composite c_c and an energy good c_k. The energy good can be supplied by one of two technologies, $k \in \{\ell, g\}$, where ℓ denotes electricity and g denotes gas. Each household owns one technology at a time but may switch between them at a cost.

Electricity has a constant price $q_\ell = \overline{q}_\ell$, while gas prices are stochastic:

$$q_g(\gamma) = \gamma\, \overline{q}_g, \tag{4}$$

where $\gamma \in \{\gamma^{\text{low}}, \gamma^{\text{high}}\}$ denotes the gas price regime. The shock γ follows a two-state Markov chain:

$$P = \begin{pmatrix} 1 - \pi^1 & \pi^1 \\ \pi^0 & 1 - \pi^0 \end{pmatrix}, \tag{5}$$

where π^1 is the probability of moving from a low- to a high-price regime, and π^0 the reverse.

Electricity prices remain constant and are interpreted as regulated retail tariffs that shield consumers from wholesale volatility, consistent with the empirical evidence in Section 2. Gas prices, in contrast, are market-based and subject to exogenous volatility. The model is solved in partial equilibrium: households take both prices as given.

I treat energy prices as exogenous. This choice is motivated by both empirical and conceptual considerations. Empirically, U.S. households represent about 15% of total natural gas demand, compared with roughly 30% for the industrial sector (EIA, 2023). As a result, changes in residential consumption are too small to materially influence aggregate gas prices. Similarly, electricity prices faced by end-use consumers reflect regulated tariffs and infrastructure costs more than short-run demand fluctuations. Conceptually, the focus of the paper is on households' heterogeneous responses to volatility, not on general-equilibrium feedbacks through energy markets. Modeling prices as exogenous therefore isolates the distributional and welfare consequences of volatility from supply-side dynamics.

Preferences. Preferences are defined over a composite consumption index c, aggregating non-energy and energy goods according to the non-homothetic CES structure of Comin, Lashkari, and Mestieri (2021):

$$(1-\theta)^{\frac{1}{\mu}} \left(\frac{c_c}{c}\right)^{\frac{\mu-1}{\mu}} + \theta^{\frac{1}{\mu}} \left(\frac{c_k}{c^{\eta}}\right)^{\frac{\mu-1}{\mu}} = 1. \tag{6}$$

Here, μ governs the elasticity of substitution between energy and non-energy goods, θ determines the share of energy in the composite, and η captures the degree of non-homotheticity. When $\eta < 1$, energy is “necessity-like,” implying that the energy expenditure share declines with income. This specification is strictly non-homothetic: marginal budget shares change smoothly with income, allowing the model to match Engel curve patterns across the entire distribution.[2]

Lifetime utility is:

$$U = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\sigma}}{1-\sigma}, \tag{7}$$

with coefficient of relative risk aversion σ and discount factor β.

Energy choice. At the beginning of each period, households choose whether to continue using its current technology k or to switch to the alternative $k' \neq k$. Switching is costly along two distinct dimensions. First, it requires the household to pay a fixed financial cost f. This cost does not depend on the household’s income or on which direction the switch takes place (from gas to electricity or from electricity to gas). Economically, it can be interpreted

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[2] By contrast, Stone–Geary preferences impose a hard subsistence level and are asymptotically homothetic. I was not able to capture the Engel curve with Stone-Geary preferences, and therefore turned to non-homothetic CES preferences.

as the upfront outlay associated with replacing heating equipment, upgrading infrastructure, or undertaking other installation expenses.

Second, switching entails a non-pecuniary cost that reflects households' heterogeneous tastes for different fuels. I model this by assuming that when evaluating the alternative technology k', the household draws a taste shock $\zeta_{k'}$ from a Type I Extreme Value (Gumbel) distribution with location parameter $\mu_{k'}$ and scale parameter λ. The location parameters $\mu_{k'}$ shift average preferences toward one technology or the other, while the scale parameter λ governs the degree of dispersion in idiosyncratic tastes across households. A larger λ implies more heterogeneity in household preferences, and hence less responsiveness of aggregate switching behavior to differences in relative prices.

Together, these two costs capture both the financial and the subjective barriers to fuel switching. The financial cost f ensures that households do not switch technologies too frequently in response to transitory shocks, while the taste shocks introduce a smooth, probabilistic choice structure rather than a knife-edge decision rule. This formulation follows the standard random utility framework of Adda and Cooper (2000) and allows the model to match the observed distribution of fuel choices across households.

Budget constraint and composite expenditure. Given composite c, energy type k, and gas shock γ, the minimum expenditure required to attain c is:

$$E(c,k;\gamma) = \Big[(1-\theta)\, c^{(1-\mu)} + \theta\, c^{(1-\mu)\eta}\, q_k(\gamma)^{\,1-\mu}\Big]^{\frac{1}{1-\mu}}\,, \tag{8}$$

where $q_k(\gamma) = q_\ell$ if $k = \ell$, and $q_k(\gamma) = q_g(\gamma)$ if $k = g$.

Intuitively, the term in brackets balances the relative importance of non-energy and energy goods (calibrated with $(1-\theta)$ and θ), their relative necessity (calibrated with η), and the price of the energy technology chosen.

The budget constraint and borrowing constraints are:

$$E(c,k;\gamma)+a'=(1+r)a+z, \qquad a'\geq -\phi, \tag{9}$$

where a' is next-period assets and ϕ is the borrowing limit.

Recursive problem. Let $V(a,z,k;\gamma)$ denote the value function at the start of a period. The household's state consists in its assets a, its idiosyncratic productivity z, its current energy type $k\in\{g,\ell\}$ and the aggregate gas shock γ. The household compares the value of staying with k or switching to k':

$$V(a,z,k;\gamma)=\max_{\{\text{keep, switch}\}}\Big\{\nu(a,z,k;\gamma),\ \nu(a-f/(1+r),z,k';\gamma)+\zeta_{k'}\Big\}, \tag{10}$$

where $\nu(a,z,k;\gamma)$ is the value conditional on owning energy type k and is defined as:

$$\nu(a,z,k;\gamma)=\max_{c,\,a'\geq-\phi}\frac{c^{1-\sigma}-1}{1-\sigma}+\beta\,\mathbb{E}\left[V(a',z',k;\gamma')\right], \tag{11}$$

subject to the budget and no-borrowing constraints (9) and shock processes for z (3) and γ:

$$\Pr(\gamma'=\gamma_j|\gamma=\gamma_i)=P_{ij} \tag{12}$$

where P is defined in (5).

Ergodic distribution. Given the parameterization, I solve the model for its ergodic (stationary) distribution. Because energy prices are exogenous, the model does not impose market clearing in energy markets. Instead, equilibrium requires internal consistency between household decision rules, the exogenous processes governing income and gas price volatility, and the resulting cross-sectional distribution of household states.

Formally, the ergodic distribution is defined by: (i) value and policy functions for consumption, saving, and fuel choice that solve the household's dynamic programming problem; (*ii*) expectations over future income and gas prices consistent with their stochastic processes, as given by equations (3) and (5); and (*iii*) a stationary distribution $\Psi(a, z, k; \gamma)$ over the individual state space that is invariant under these optimal decision rules and exogenous transitions in (z, γ).

In partial equilibrium, the equilibrium object is entirely determined by household behavior. Given exogenous energy prices, each household optimally chooses whether to switch technologies and how much to consume and save. The invariant distribution Ψ aggregates these individual decisions into a stable cross-sectional pattern of assets, income, and energy choices. In this sense, equilibrium reduces to the internally consistent mapping from household states and shocks to optimal policies and, ultimately, to a stationary distribution of economic outcomes.

3.2 Optimal decision rules and aggregates

I now look at the inner workings of the model and its implications for households' energy-related decisions. Given a state $(a, z, k; \gamma)$, households first compute the value from switching energy type and from not switching energy type. This involves solving the consumption-savings problem in both cases. They then compare both values given the taste shock drawn this period.

Consumption-savings problem. The consumption-savings problem is described in (11). I first show households' savings decisions given a consumption index c, and then show the consumption decision for c_c and c_k, given a consumption index c.

The Euler equation in this problem is:

$$\frac{c_t^{-\sigma}}{\partial E(c_t, k_t; \gamma_t)/\partial c_t} \geq \beta\,(1+r)\,\mathbb{E}_t\left[\frac{c_{t+1}^{-\sigma}}{\partial E(c_{t+1}, k_{t+1}; \gamma_{t+1})/\partial c_{t+1}}\right], \tag{13}$$

with equality whenever the borrowing constraint does not bind (i.e., $a' > -\phi$). Equation (13) says that when $a' > -\phi$, the household equates the marginal utility of one more dollar of expenditure today (left-hand side) to the discounted expected marginal utility value of a dollar saved (right-hand side). The non-homothetic structure enters through the partial derivative of the expenditure function E with respect to the consumption index c: because energy is closer to a necessity, this rate of change falls less rapidly with c than in a homothetic CES, and depends on which technology k is in place and on the realized gas shock γ. Fuel switching affects the Euler equation only through this and on the resource constraint, via the fixed cost f in periods when switching occurs.

The expenditure on c_c and c_k is found as the values minimizing the expenditure on c, and are given by:

$$c_c = (1-\theta)\, E(c,k;\gamma)^{\mu}\, c \tag{14}$$

$$c_k = \theta \left[\frac{E(c,k;\gamma)}{q_k(\gamma)}\right]^{\mu} c^{\eta}, \tag{15}$$

Of particular interest is the expression for energy consumption, (15). A higher value of $q_k(\gamma)$ is associated with a lower energy consumption – this is the intensive channel through which energy prices affect energy consumption.

The decision to switch. Households face idiosyncratic taste shocks $\zeta_k \sim \text{Gumbel}(\lambda, \mu_k)$, which affect the utility from switching to each energy source k. Given those shocks, the probability that a household switches from energy type k to $k' \neq k$, conditional on its asset level a, idiosyncratic income state z, and the aggregate gas price shock γ, is given by

$$\Pr(\text{switch} \mid a, z, k; \gamma) = \frac{1}{1 + \exp\left[\frac{\nu(a,z,k;\gamma) - \nu(a-f,z,k';\gamma) - \mu_{k'}}{\lambda}\right]}.$$

This switching decision depends fundamentally on the difference in the value of staying with the current energy type versus switching:

$$\Delta\nu(a,z,k;\gamma) \equiv \nu(a,z,k;\gamma) - [\nu(a-f,z,k';\gamma) + \mu_{k'}]$$

The probability of switching is decreasing in $\Delta\nu$: if $\Delta\nu(a,z,k;\gamma)$ increases, the relative value of the current energy source rises, making switching less attractive; if $\Delta\nu(a,z,k;\gamma)$ decreases, switching becomes more likely. As the gas shock increases, both the value from keeping gas and the value from switching decrease, though at varying rates, thereby leading to an increase in the probability to switch to electricity. For a household currently owning gas, i.e. with $k = g$, the value from keeping gas decreases faster than the value from switching to electricity because a higher gas shock γ leads to a decrease in energy consumption.

Heterogeneity and income effects. The model also implies systematic differences in switching behavior across the income distribution. Because preferences are non-homothetic, poorer households devote a larger share of their budget to energy consumption. As a result, they experience a larger utility loss when gas prices rise, and are therefore more responsive to gas price volatility. Richer households, for whom energy constitutes a smaller share of expenditure, are less affected by the same price shock and less likely to switch. This mechanism—whereby exposure to price risk interacts with non-homothetic preferences—generates the precautionary electrification pattern observed in the data.

Aggregates. Given the stationary distribution $\Psi(a,z,k;\gamma)$, aggregate quantities are obtained by integrating optimal household policy functions for non-energy consumption $c_c(a,z,k;\gamma)$, energy consumption $c_k(a,z,k;\gamma)$, asset accumulation $a'(a,z,k;\gamma)$, and switching behavior over the cross-sectional distribution of households across assets, income, energy type, and gas price states.

Gas consumption. Aggregate gas demand, C_g, consists of two groups: households who currently use gas and choose to keep it, and households who initially use electricity but decide to switch. Formally,

$$C_g = \int c_k(a, z, g; \gamma)\ \Pr(\text{keep} \mid a, z, g; \gamma)\, \mathrm{d}\Psi + \int c_k(a, z, g; \gamma)\ \Pr(\text{switch} \mid a, z, \ell; \gamma)\, \mathrm{d}\Psi. \quad (16)$$

The first term captures "stayers" who retain gas, and the second term accounts for "switchers" into gas.

Electricity consumption. Similarly, total electricity demand combines electricity stayers and switchers out of gas:

$$C_\ell = \int c_k(a, z, \ell; \gamma)\ \Pr(\text{keep} \mid a, z, \ell; \gamma)\, \mathrm{d}\Psi + \int c_k(a, z, \ell; \gamma)\ \Pr(\text{switch} \mid a, z, g; \gamma)\, \mathrm{d}\Psi. \quad (17)$$

Energy expenditure. Aggregate energy expenditure E at a given time is the total dollar value of energy consumed, weighted by prices:

$$E = \int \Big[q_g(\gamma)\, c_k(a, z, g; \gamma) + \overline{q}_\ell\, c_k(a, z, \ell; \gamma) \Big]\, \mathrm{d}\Psi. \quad (18)$$

Non-energy expenditure. Aggregate non-energy consumption is given by

$$C_c = \int c_c(a, z, k; \gamma)\, \mathrm{d}\Psi. \quad (19)$$

Energy share. The steady-state aggregate share of energy expenditure in total consumption is then

$$s_E = \frac{E}{E + C_c}. \quad (20)$$

These aggregates play a central role in calibration and interpretation. The relative price of gas, $\overline{q}_g$, and the electricity price, $\overline{q}_\ell$, jointly determine the steady-state ratio of aggregate gas to electricity demand, thereby disciplining the model's extensive margin of energy choice. The overall level of energy prices determines the aggregate energy expenditure share s_E, the key moment reflecting non-homotheticity in the data: as income rises, households devote a smaller fraction of expenditure to energy.

In this way, relative prices primarily identify the parameters governing the switching margin between fuels, while the aggregate energy share identifies the parameters (θ, η, μ) governing energy Engel curves. The cross-sectional distribution of energy technologies thus provides empirical leverage to pin down both substitution patterns and heterogeneity in exposure to price volatility.

3.3 Quantification

I calibrate the model to U.S. data around the 2019–2023 period, treating this as the relevant steady state. The model is annual, and the calibration proceeds in two steps. First, I assign values to a subset of parameters, fixing them at standard values or borrowing from the literature. Second, conditional on these assignments, I estimate the remaining parameters by simulated method of moments (SMM), choosing them so that the model reproduces a set of targeted empirical moments. The full parameterization is summarized in Table 3.

Table 3: Model parameterization

I. Assigned parameters			II. Estimated parameters		
σ	1	crra coefficient	β	0.956	discount factor
r	0.03	interest rate	η	0.040	energy non-homotheticity
ϕ	0	borrowing constraint	$\overline{q}_g$	0.034	unit cost of gas
μ	0.275	energy/non-energy elast. subst.	$\overline{q}_\ell$	0.030	unit cost of electricity
ρ_z	0.920	income shock persistence	μ_g	0.185	switching taste shock, gas
σ_z	0.285	income shock s.d.	μ_ℓ	-0.260	switching taste shock, elec
$\{\pi^0, \pi^1\}$	$\{0.4, 0.1\}$	gas regime probabilities	f	0.020	switching fixed cost
$\{\gamma^{\text{low}}, \gamma^{\text{high}}\}$	$\{0.93, 1.28\}$	gas regime states	λ	0.034	switching taste shock scale
θ	0.07	energy utility share			

Notes: Assigned parameters are fixed to standard values from the literature. Estimated parameters are calibrated using simulated method of moments (SMM) to match U.S. data for 2019–2021, targeting aggregate expenditure ratios, wealth-to-income levels, and the observed distribution of energy technologies.

Assigned parameters. Several parameters are set to conventional or directly observable values. Preferences are logarithmic ($\sigma = 1$), and the annual real interest rate is fixed at $r = 0.03$. Households cannot borrow ($\phi = 0$). The elasticity of substitution between energy and non-energy goods is $\mu = 0.275$, consistent with Känzig (2023), who estimate complementarity between energy and non- consumption.

Idiosyncratic income shocks follow an AR(1) process with persistence $\rho_z = 0.92$ and standard deviation $\sigma_z = 0.285$, consistent with estimates from the heterogeneous-agent macroeconomics literature. Gas prices follow a two-state Markov process with levels $\gamma^{\text{low}} = 0.93$ and $\gamma^{\text{high}} = 1.28$, and transition probabilities $\pi^0 = 0.1$ and $\pi^1 = 0.4$. These imply an expected duration of approximately 2.5 years for the high-price regime and a stationary probability of 20%, in line with historical gas price data. The utility weight on energy, $\theta = 0.07$, is chosen to match the average share of household expenditure devoted to energy in U.S. consumption data (Comin, Lashkari, and Mestieri, 2021).

Estimated parameters. The remaining parameters are estimated via simulated method of moments. The discount factor $\beta = 0.956$ matches the aggregate wealth-to-income ratio of 5.53 observed in the 2019 Survey of Consumer Finances. The non-homotheticity parameter $\eta = 0.04$ governs how the energy expenditure share declines with income and is chosen to reproduce the observed energy budget shares across income quintiles—10% for the bottom quintile and 4% for the top quintile. The unit prices of gas and electricity, $\overline{q}_g = 0.034$ and $\overline{q}_\ell = 0.030$, are calibrated to match the observed energy-to-non-energy expenditure ratio (0.07 in the data versus 0.06 in the model) and the electricity-to-gas expenditure ratio for heating (0.89 in the data versus 0.86 in the model). Switching behavior disciplines the remaining parameters. The location parameters of the taste shock distribution, $(\mu_g, \mu_\ell) = (0.185, -0.260)$, the fixed switching cost $f = 0.020$, and the scale of taste heterogeneity $\lambda = 0.034$ are jointly identified from the observed prevalence of gas heating (59%), the aggregate annual switching probability (15%), and the relative likelihood of gas adoption across income groups (a Q5/Q1 ratio of 1.30). Together, these moments ensure that the model replicates both the overall fuel mix and its income gradient.

Table 4: Targeted moments

Targeted moment	Data	Model
Wealth-to-income ratio	5.53	5.53
Energy/non-energy expenditure ratio	0.07	0.06
Electricity/gas expenditure ratio (heating only)	0.89	0.86
Energy expenditure share, Q1	0.10	0.11
Energy expenditure share, Q5	0.04	0.04
Probability of switching	0.15	0.15
Share with gas	0.59	0.59
Share with gas, Q5/Q1	1.30	1.30

Notes: Targeted moments are based on U.S. data for 2019–2023. The model reproduces both aggregate expenditure ratios and cross-sectional patterns in energy use across income quintiles.

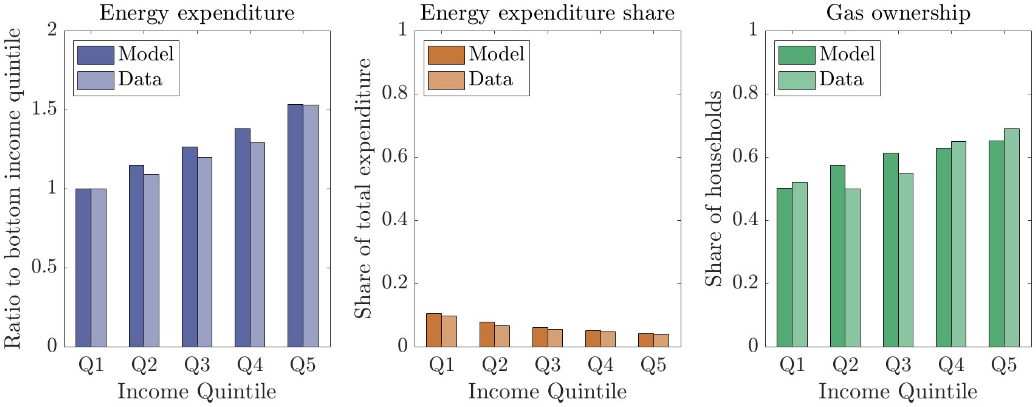
Model fit. Figure 4 compares the model's predictions to the data across income quintiles along three dimensions: total energy expenditure, the energy expenditure share, and the share of households using gas. The model closely replicates all three empirical patterns. In particular, it matches the decline in the energy expenditure share with income and reproduces the strong income gradient in gas adoption—two of the key motivating facts documented in Section 2.

3.4 Precautionary electrification in the model

This section quantifies how a permanent rise in gas price volatility affects household energy choices and welfare. Using the calibrated model, I show that higher volatility induces households to substitute toward electricity, and that this precautionary electrification response is strongest among poorer households.

I consider an unanticipated, permanent 10% increase in the volatility of gas prices. To do so, I increase the probability to transition from the high to low state and the probability to transition from low to high state, so as to keep the average price constant.

Figure 4: Model Fit by Income Quintile: Energy Use, Share, and Energy Type



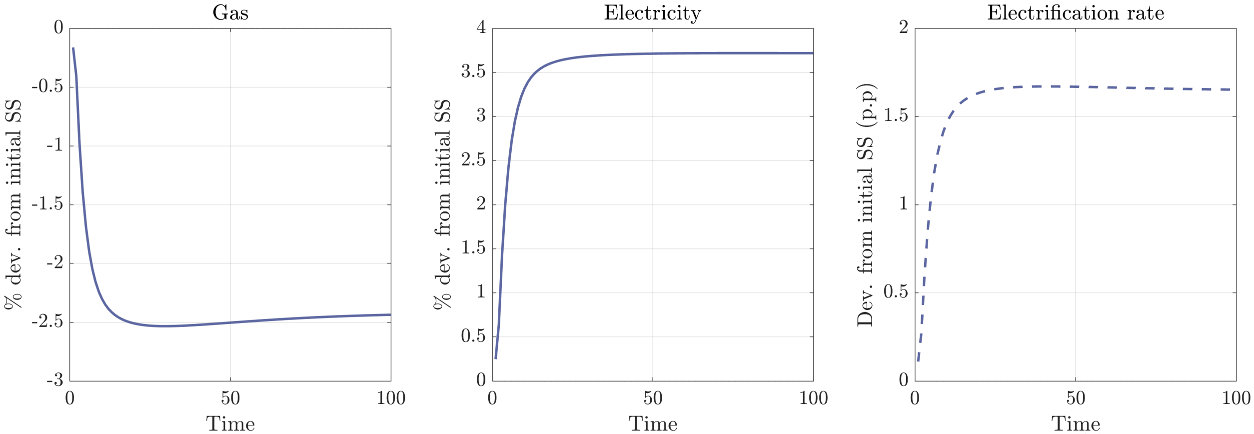
Notes: The figure compares model-implied outcomes (lighter bars) with data counterparts (darker bars), by income quintile. The model reproduces the increasing energy expenditure, the declining energy expenditure share and the higher prevalence of gas use among richer households. All quantities are expressed in steady state and correspond to the 2019–2023 calibration period.

The transition is computed in the standard way. I first solve for the new stationary equilibrium under both counterfactuals. I then construct the perfect-foresight transition path by backward induction over a finite horizon, using time-indexed policy functions. Finally, I simulate the economy forward from the initial steady state to trace out the evolution of aggregates and distributions.

Aggregate effects. Figure 5 plots the transition paths for gas and electricity consumption, as well as the change in the electrification rate. The increase in gas price risk reduces gas consumption and raises electricity consumption, driven by households switching away from the riskier technology. In short, greater volatility shifts demand toward electricity, consistent with a precautionary motive operating at the extensive margin. In particular, a 10% increase in the volatility of gas prices leads to an increase in the electrification rate of 1.7 p.p in the model.

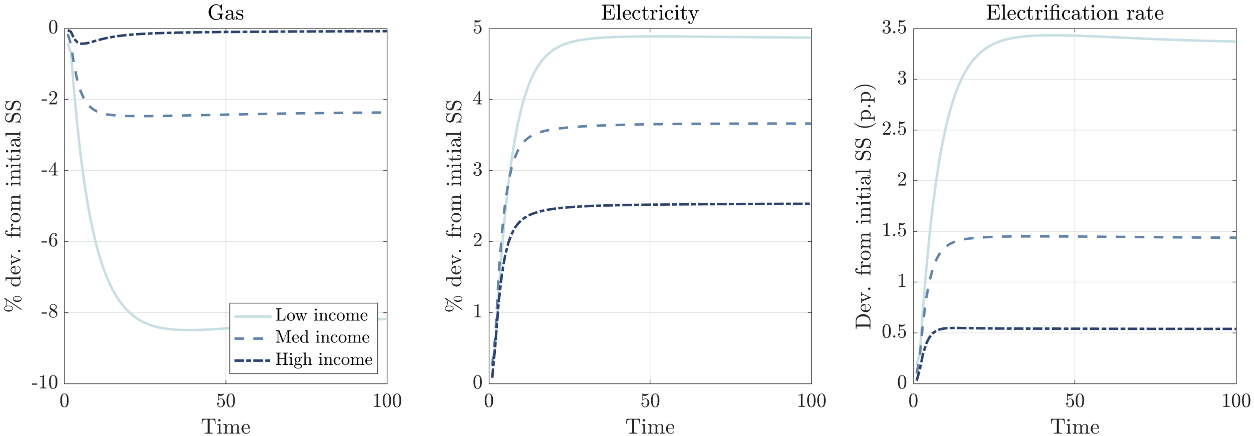
Distributional effects. Figure 6 decomposes these responses by income quintile. Aggregate adjustments mask substantial heterogeneity: poorer households exhibit a much larger increase in electrification (about 3.4 p.p) than richer ones (around 0.5 p.p). Consequently,

Figure 5: The aggregate impact of a 10% increase in gas price volatility



Notes: The figure reports model-implied transition dynamics after a permanent 10% increase in gas price volatility, holding mean prices constant. Higher volatility induces a gradual reallocation from gas to electricity, leading to lower aggregate gas consumption and higher electricity use in the new steady state.

Figure 6: The distributional impact of a 10% increase in gas price volatility



Notes: The figure shows the response of energy consumption by income quintile following a 10% increase in gas price volatility. Low-income households substitute strongly toward electricity, while higher-income households' gas use is relatively stable or slightly higher due to lower expected realizations of gas prices.

electricity consumption rises disproportionately among low-income households, while their gas consumption falls. By contrast, the gas consumption of richer households barely moves. These heterogeneous responses reflect the interaction between income-dependent energy shares and the precautionary motive embedded in non-homothetic preferences.

Welfare effects. Welfare is evaluated in consumption-equivalent terms, following Benabou (2002). For each household i, let V_i denote lifetime utility under the optimal policy functions. I compute the consumption-equivalent level ω_i that yields the same lifetime utility if the household consumed a constant amount ω_i each period:

$$V_i = \sum_{t=0}^{\infty} \beta^t \frac{\omega_i^{1-\sigma} - 1}{1-\sigma} \tag{21}$$

Welfare changes are expressed as percentage differences in ω_i between the baseline and the high-volatility steady states.

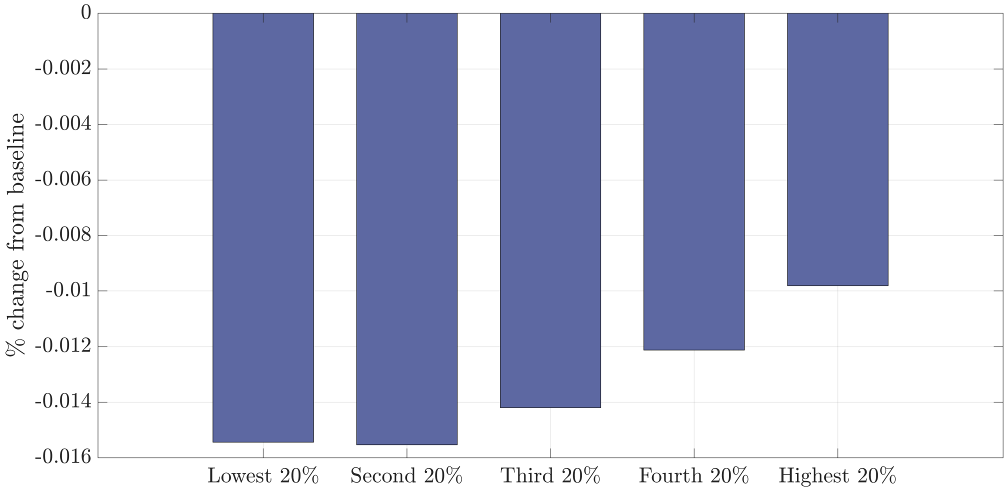
Figure 7 presents welfare changes by income quintile. On average, the increase in volatility slightly reduces aggregate welfare, but the distributional impact is strongly regressive. Poorer households experience the largest welfare losses when gas price risk rises, while wealthier households are only marginally affected.

The intuition is twofold. First, low-income households are more exposed to volatility because they are more likely to adopt electricity as a form of precautionary self-insurance. Although this strategy stabilizes their energy expenditures, it reduces utility since gas is the preferred heating source in expectation. Second, higher-income households can smooth consumption and remain on gas despite greater price uncertainty, avoiding the associated utility loss. Consequently, greater gas price volatility acts as a regressive shock that widens welfare disparities across the income distribution.

4 Policy

In this section, I use the calibrated model to evaluate two short-term energy relief policies inspired by those implemented across Europe during the 2021–22 energy crisis: a flat transfer and a proportional subsidy. Both measures aim to cushion households against temporary gas price spikes that disproportionately burden low-income households. However,

Figure 7: Consumption-equivalent welfare change by income



Notes: The figure reports steady-state changes in consumption-equivalent welfare across income quintiles following a 10% increase in gas price volatility. Welfare is computed as the constant level of consumption yielding the same lifetime utility, as in Benabou (2002).

they introduce an important policy trade-off: while both policies provide immediate relief and raise welfare, they also weaken households' precautionary motive to adopt electricity as protection against future volatility. The flat transfer is more redistributive and yields higher welfare gains—especially for poorer households—but it also slows electrification more strongly. The proportional subsidy, by contrast, better preserves electrification incentives but delivers smaller welfare improvements.

Policy design. The first intervention is an unconditional transfer targeted to gas users. When the gas price is in the high state ($\gamma = \gamma^{\text{high}}$), affected households receive a lump-sum transfer T, modifying their budget constraint to

$$E(c, g; \gamma^{\text{high}}) + a' = (1 + r)a + z + T. \tag{22}$$

The second policy is a proportional subsidy that reduces the effective gas price by a fraction

τ during high-price periods:

$$E(c, g; (1-\tau)\gamma^{\text{high}}) + a' = (1+r)a + z. \tag{23}$$

In both cases, the expected fiscal cost is calibrated to 20% of aggregate energy expenditures in the baseline ergodic distribution. Policies are triggered only in the high-price regime and apply directly to gas users.

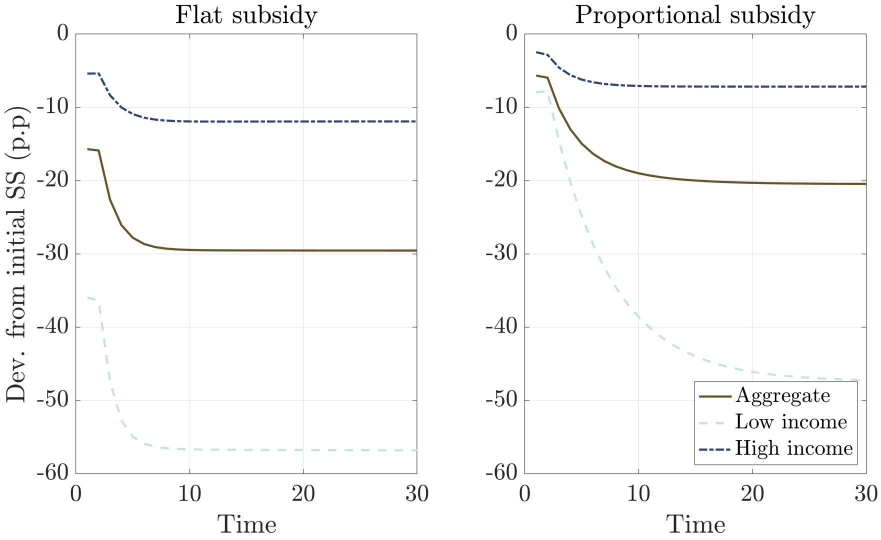
Relief policies and electrification. Figure 8 plots steady-state changes in electrification following the introduction of each policy. Both interventions weaken households' incentive to self-insure against gas price risk through switching to electricity. However, the magnitude of the response differs: the flat transfer (left panel) reduces the electrification rate by roughly 30 percentage points, compared to about 20 points under the proportional subsidy (right panel).

The stronger response under the flat transfer reflects its uniform income effect: poorer households experience a larger proportional relaxation of their budget constraint, which raises the relative attractiveness of gas (the preferred technology given taste shocks). As a result, they are less inclined to switch to electricity for precautionary reasons.

Relief policies and welfare. Table 5 summarizes welfare effects in consumption-equivalent terms, by income quintile and in aggregate. Both policies improve welfare relative to the no-relief baseline, but the magnitude differs substantially. The flat transfer yields larger gains across all quintiles, with the largest benefits accruing to the poorest households. By contrast, the proportional subsidy provides modest improvements, concentrated among middle- and high-income groups with higher gas consumption.

The difference arises because the flat transfer directly relaxes liquidity constraints, enhancing welfare even for households with limited energy demand. In contrast, the proportional

Figure 8: Electrification rates under flat and proportional subsidies



Notes: The figure reports steady-state changes in the electrification rate under the two policy regimes. Both are budget-neutral in expectation (20% of baseline energy spending) and operate only when gas prices are high. The flat transfer induces a sharper decline in electrification by providing stronger income relief to gas users, particularly among lower-income households.

subsidy primarily benefits those already consuming substantial amounts of gas energy.

These experiments highlight a fundamental policy trade-off between short-term relief and long-term electrification. A flat transfer delivers stronger welfare gains but discourages electrification by reducing the incentive to switch. A proportional subsidy better preserves electrification incentives but provides weaker insurance and smaller welfare improvements. The optimal policy choice therefore depends on the policymaker's weighting of immediate distributional objectives versus longer-term decarbonization and resilience goals.

5 Conclusion

This paper documents and quantifies a precautionary electrification channel: when gas prices are more volatile than electricity prices, households shift toward electricity as a form of self-insurance. A heterogeneous-agent model with non-homothetic preferences rationalizes these facts and reproduces key cross-sectional patterns in energy use and expenditure shares.

Table 5: Welfare effects of relief policies (% deviation from baseline)

	Flat transfer	Proportional subsidy
Lowest 20%	2.56	0.47
Second 20%	1.94	0.43
Third 20%	1.39	0.35
Fourth 20%	0.95	0.28
Highest 20%	0.62	0.21
Aggregate	1.28	0.33

Notes: This table compares the change in welfare caused by the introduction of a flat transfer and a proportional subsidy policy. Welfare is measured in consumption-equivalent terms relative to the baseline steady state and expressed in percent deviation from the baseline steady state. Both policies are activated only when gas prices are high and are designed to have equal expected fiscal cost (20% of aggregate energy spending in the baseline).

Counterfactuals highlight two implications. First, higher gas price volatility induces a meaningful reallocation toward electricity (about 1.7 p.p. for a 10% volatility increase) and reduces welfare on average, with losses concentrated among poorer households—evidence that volatility is regressive. Second, short-term relief policies confront a clear trade-off: a flat transfer delivers larger welfare gains (especially at the bottom) but more strongly dampens electrification, whereas a proportional subsidy preserves electrification incentives better but yields smaller welfare improvements.

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Appendix A: Derivations

A.1. Optimal expenditure index

Households maximize the composite consumption index c subject to the non-homothetic CES aggregator and total expenditure E:

$$\begin{aligned} \max_{c_c, c_k} \quad & c \\ \text{s.t.} \quad & (1-\theta)^{\frac{1}{\mu}} \left(\frac{c_c}{c}\right)^{\frac{\mu-1}{\mu}} + \theta^{\frac{1}{\mu}} \left(\frac{c_k}{c^{\eta}}\right)^{\frac{\mu-1}{\mu}} = 1, \qquad E = c_c + q_k c_k. \end{aligned} \tag{24}$$

The Lagrangian is

$$\mathcal{L} = c + \rho\left[1 - (1-\theta)^{\frac{1}{\mu}} \left(\frac{c_c}{c}\right)^{\frac{\mu-1}{\mu}} - \theta^{\frac{1}{\mu}} \left(\frac{c_k}{c^{\eta}}\right)^{\frac{\mu-1}{\mu}}\right] + \lambda\left(E - c_c - q_k c_k\right), \tag{25}$$

where ρ, λ are multipliers. The first-order conditions imply

$$\frac{\rho}{\lambda} = E\frac{\mu}{1-\mu}, \qquad c_c = (1-\theta)\, E^{\mu} c^{1-\mu}, \qquad c_k = \theta \left(\frac{E}{q_k}\right)^{\mu} c^{(1-\mu)\eta}. \tag{26}$$

Using $E = c_c + q_k c_k$ yields the expenditure function:

$$E(c, k; \gamma) = \Big[(1-\theta) c^{1-\mu} + \theta\, q_k(\gamma)^{1-\mu}\, c^{\eta(1-\mu)}\Big]^{\frac{1}{1-\mu}}, \tag{27}$$

which is used in the main text.

A.2. First-order conditions and Euler equation

Conditioning on installed technology k, the household's problem is:

$$\max_{c,\, a' \geq -\phi} \; \frac{c^{1-\sigma}}{1-\sigma} \; + \; \beta\, \mathbb{E}\Big[V(a', z', k; \gamma')\Big] \quad \text{s.t.} \quad E(c, k; \gamma) + a' = (1+r)a + z. \tag{28}$$

The intratemporal first-order condition equates marginal utility to the shadow price index $P = \partial E/\partial c$:

$$c^{-\sigma} = \lambda\, P(c, k; \gamma). \tag{29}$$

The intertemporal condition, combining (29) across t and $t+1$, gives the Euler inequality:

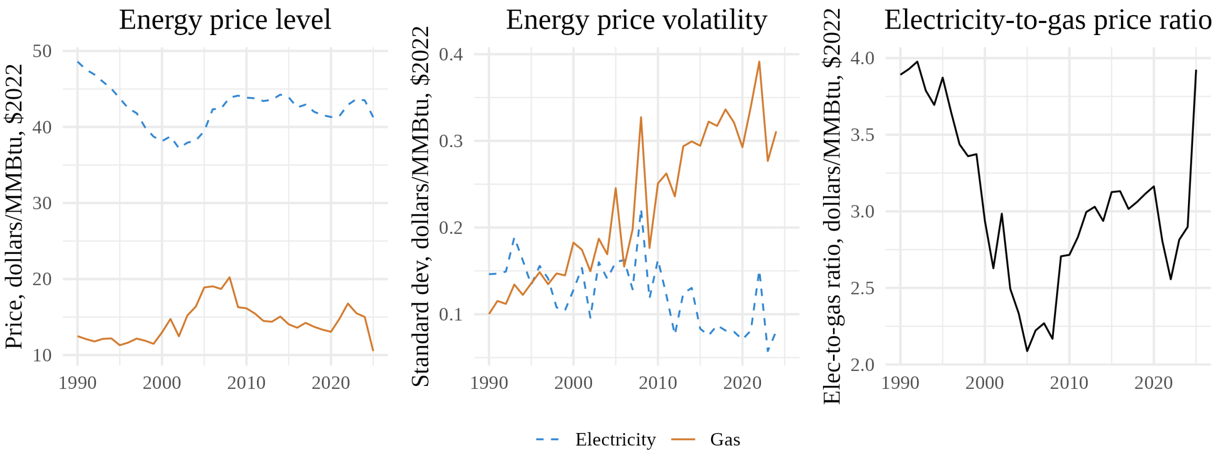
$$\frac{c_t^{-\sigma}}{P(c_t, k_t; \gamma_t)} \;\geq\; \beta(1+r)\, \mathbb{E}_t\left[\frac{c_{t+1}^{-\sigma}}{P(c_{t+1}, k_{t+1}; \gamma_{t+1})}\right], \tag{30}$$

with equality whenever the borrowing constraint does not bind ($a' > -\phi$).

Equation (30) shows that households equate the marginal utility of an additional unit of composite consumption today to its discounted expected value tomorrow, expressed in “price-of-utility” units $P(c, k; \gamma)$.

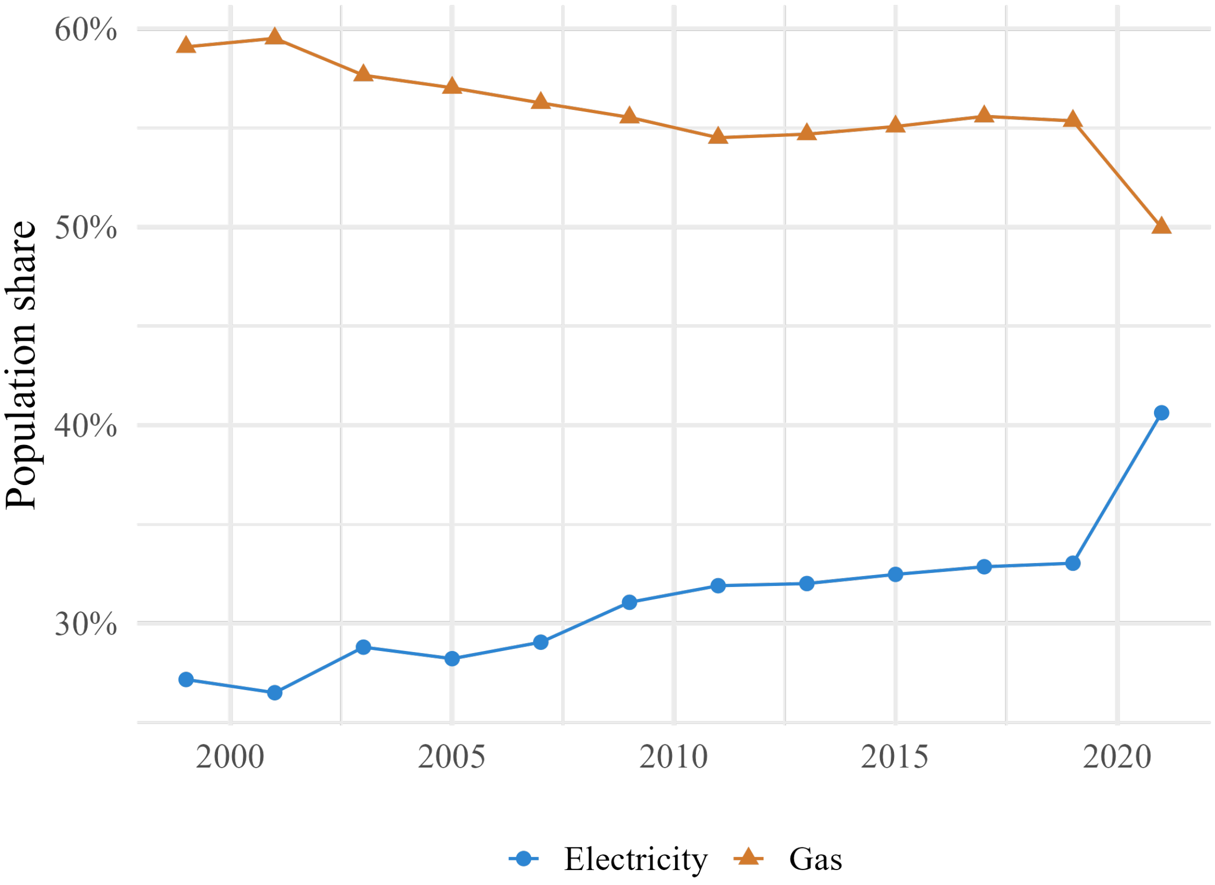
Appendix B: Additional Figures

Figure B1. Energy Price Levels, Volatility, and Relative Prices Over Time



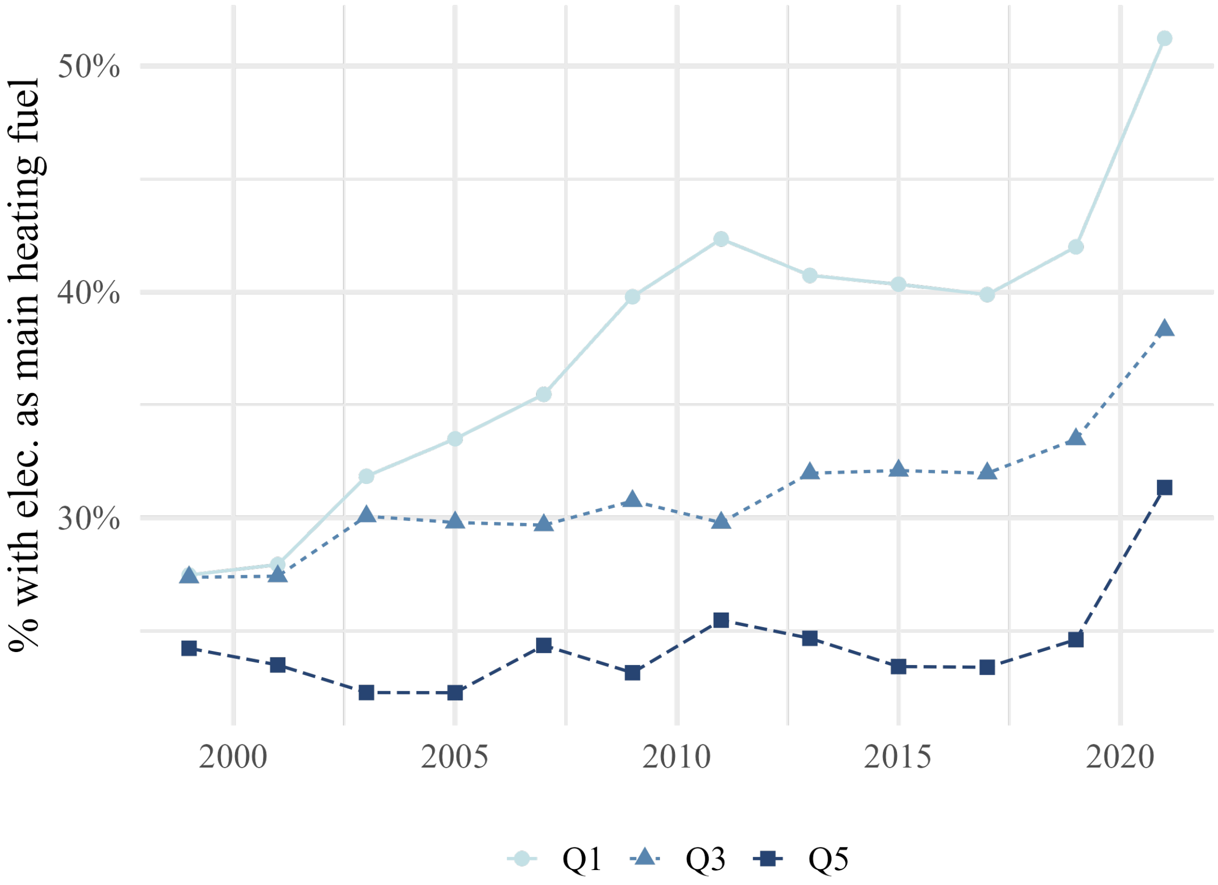
Notes: This figure displays the evolution of average energy prices in dollars per MMBtu (leftmost panel), the volatility of energy prices computed as the standard deviation of monthly energy prices within each year (middle panel), and the electricity-to-gas price ratio from 1990 to 2023 (rightmost panel). Data are from FRED.

Figure B2. Main heating fuel shares, 1999-2021



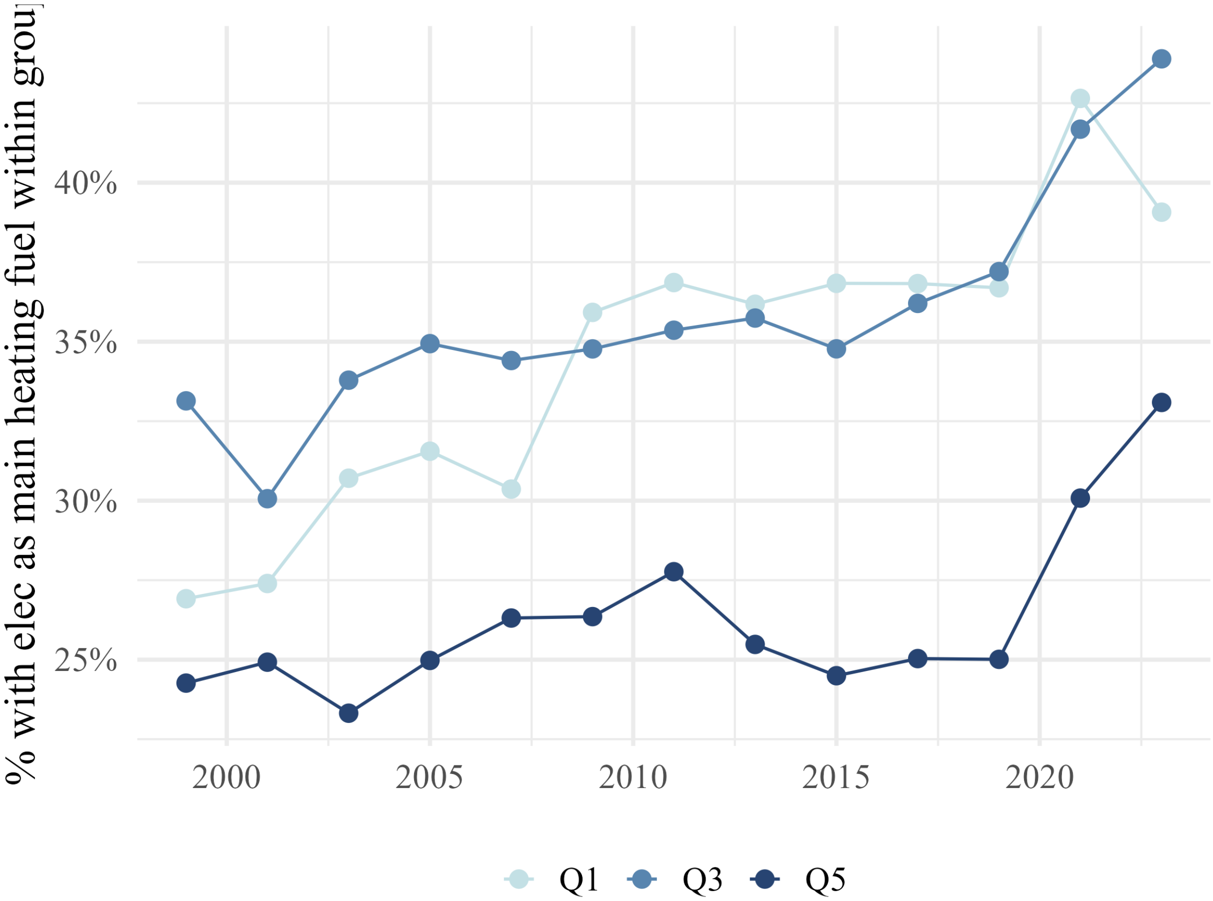
Notes: This figure shows the evolution of the main heating fuel used by households, highlighting the gradual shift away from gas heating toward electricity. Data are from the PSID.

Figure B3. Electrification rates by income quintile



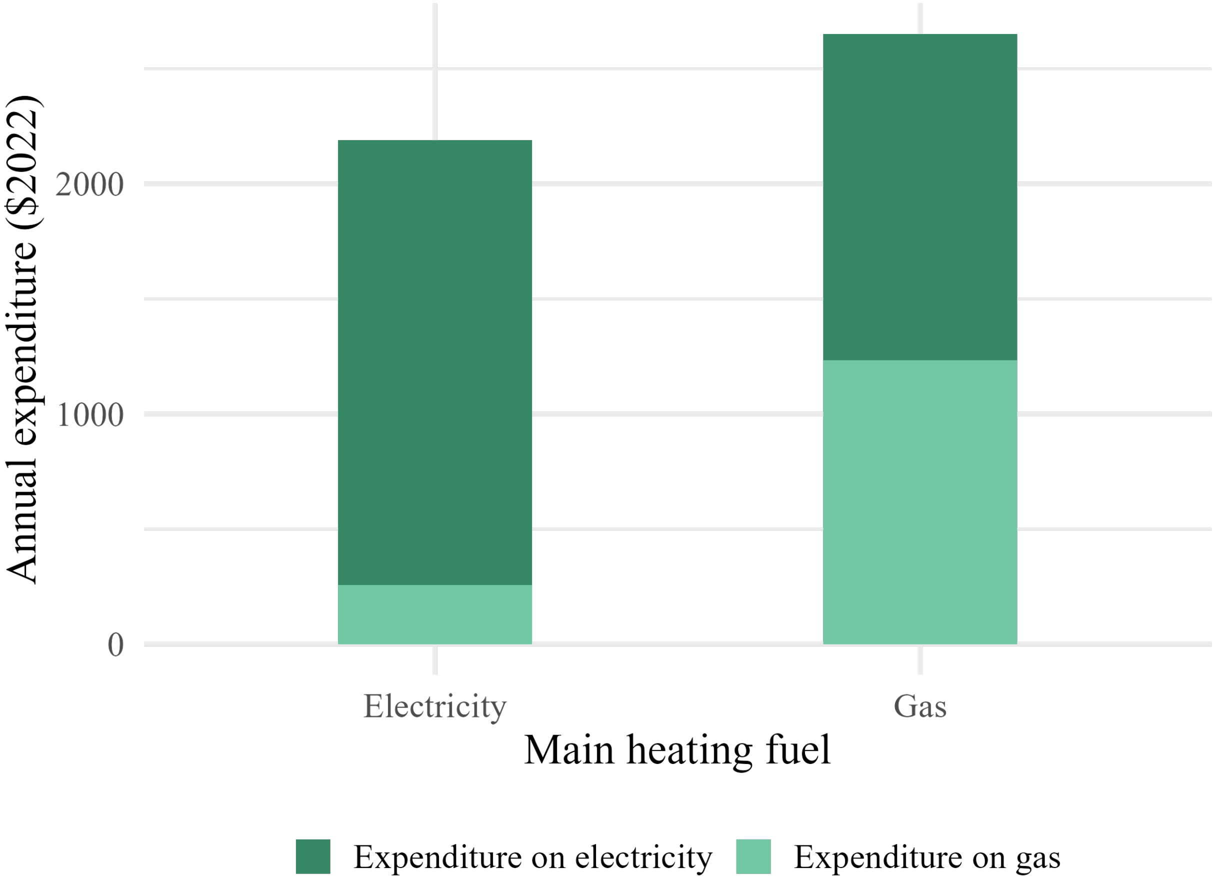
Notes: The figure plots the share of households using electricity as their main heating source across income quintiles, from 1999 to 2021. Data are from the PSID.

Figure B4. Electrification by Income Quintile Among Homeowners



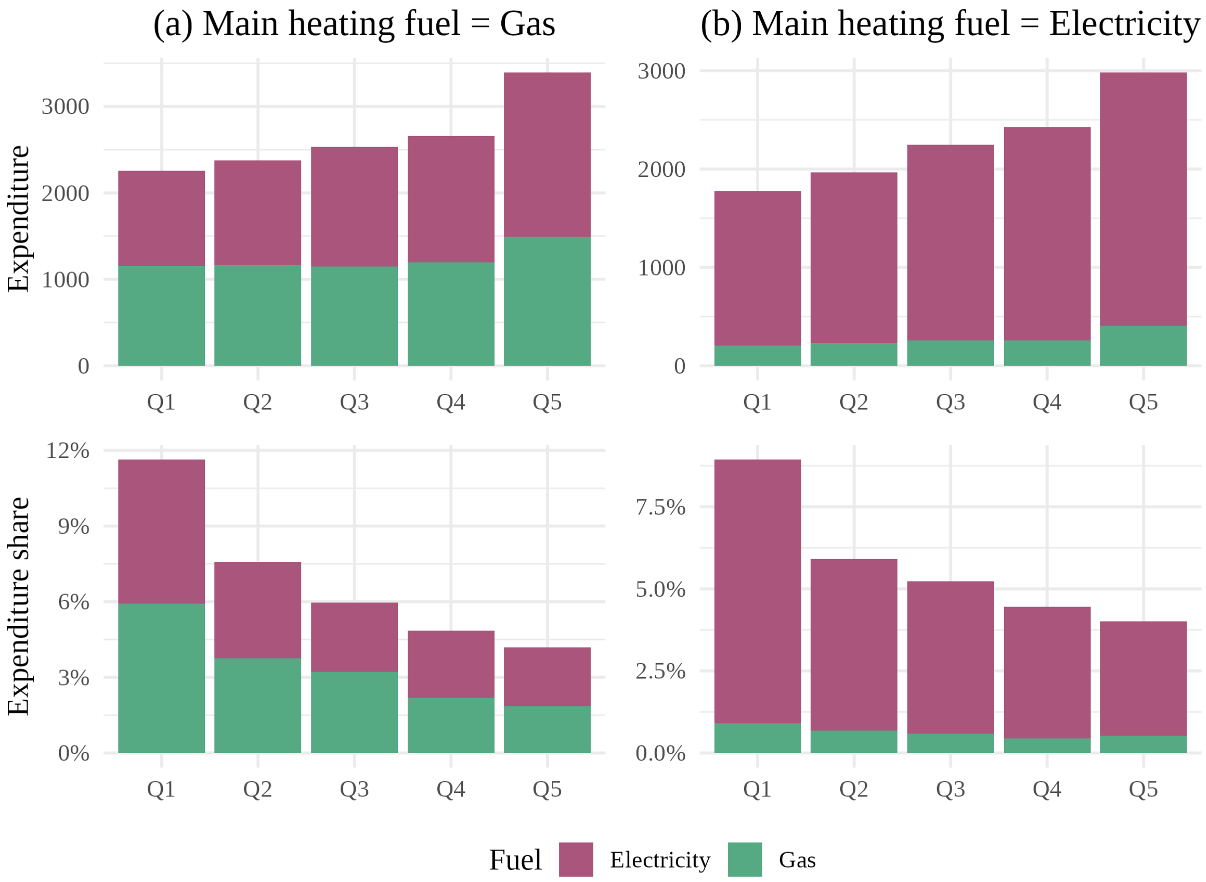
Notes: The figure plots the share of households using electricity as their main heating source across income quintiles, from 1999 to 2021, restricting the sample to homeowners only. Data are from the PSID.

Figure B5. Electricity and gas expenditure, by main heating fuel



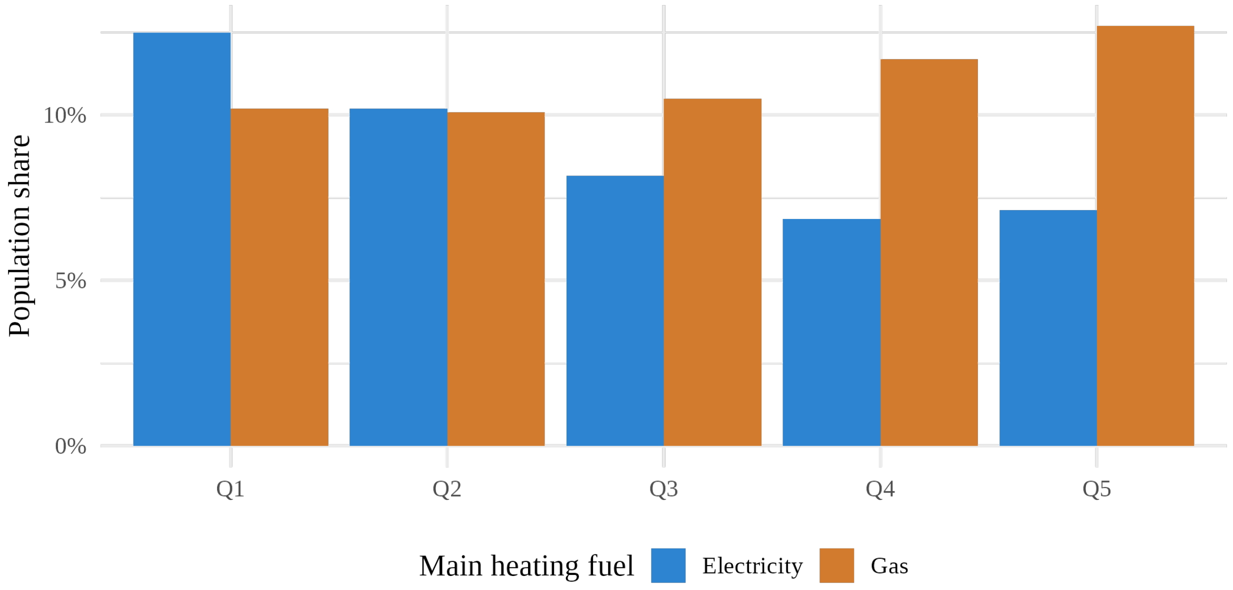
Notes: This figure shows the distribution of energy expenditure across electricity and gas, by heating fuel. Households whose main heating fuel is electricity spend a larger share of energy expenditure on electricity; while households whose main heating fuel is gas spend a larger share of energy expenditure on gas. Data are from the PSID.

Figure B6. Energy expenditure on gas and electricity, by income quintile, by main heating fuel



Notes: This figure shows the composition of energy expenditure by income quintile, by main heating fuel. The leftmost column shows total average expenditure (top) and average expenditure share (bottom) on electricity and gas for households whose main heating fuel is gas, by income quintile. The rightmost column shows total average expenditure (top) and average expenditure share (bottom) on electricity and gas for households whose main heating fuel is electricity, by income quintile. Data are from the PSID.

Figure B7. Joint distribution of heating fuel and income quintile



Notes: This figure shows the joint distribution of households over income and main heating fuel in the PSID, in 2021. Data are from the PSID.

Appendix C: Non-homothetic Energy Expenditure

In this appendix, I provide direct evidence for non-homothetic energy expenditure using the PSID. Energy expenditure exhibits non-homotheticity: the share of total expenditure devoted to energy declines with income. This is a typical characteristic of necessity goods, for which a baseline level of consumption is required regardless of income. Energy use—driven in part by heating, cooking, and basic household functions—fits naturally into this category.

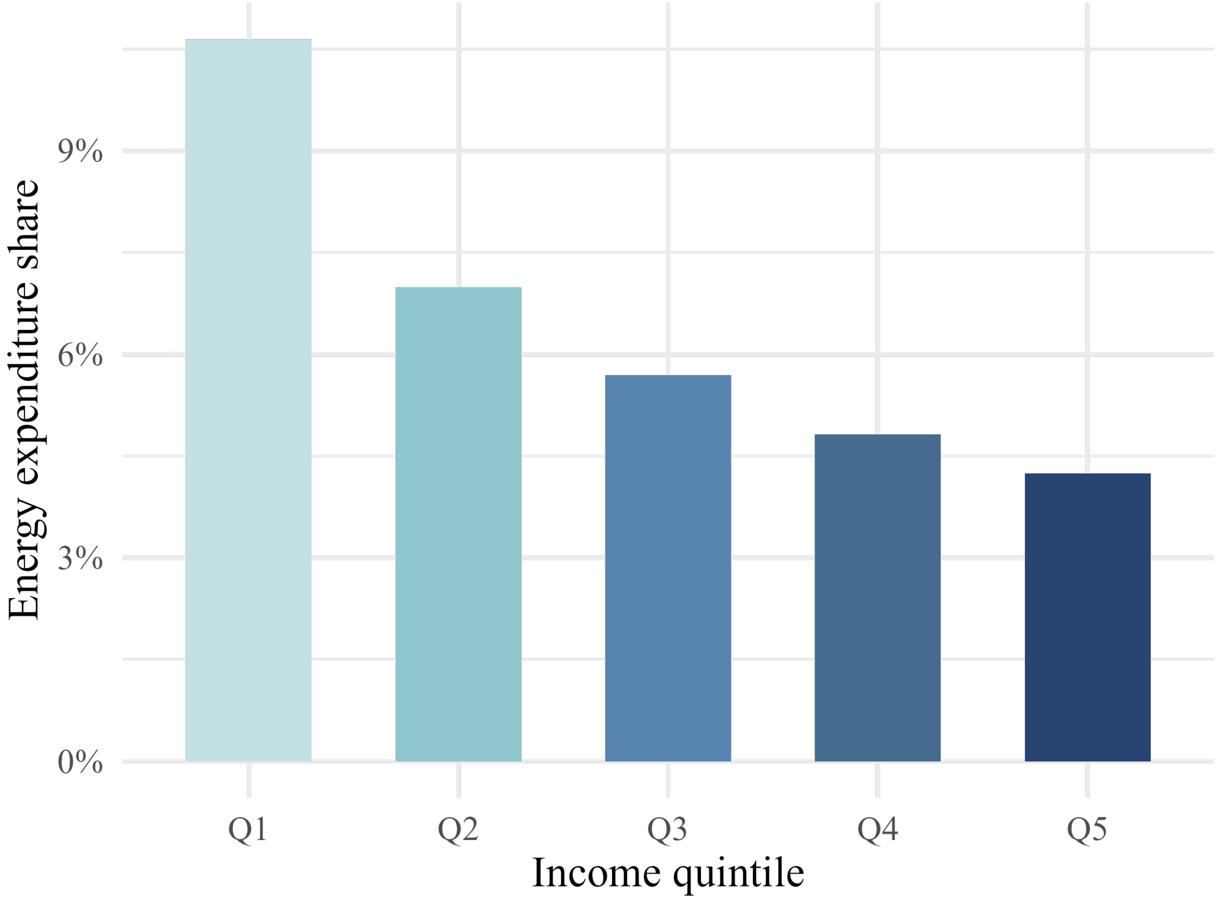
Figure **??** illustrates this pattern by presenting, for each income quintile, two key statistics: average energy expenditure (panel (a)) and average energy expenditure share (panel (b)). The expenditure measure combines annual spending on both gas and electricity. Panel (a) shows that, in absolute terms, wealthier households spend more on energy. For instance, households in the top income quintile spend roughly 1.5 times more than those in the bottom quintile. However, panel (b) reveals a sharply declining trend in the energy expenditure share: while households in the bottom quintile allocate approximately 10% of their total expenditure to energy, this share drops to around 4% for households in the top quintile.

To validate that this pattern is not driven by compositional or confounding factors, I estimate a regression of the log energy expenditure share on log income, controlling for relevant household characteristics and fixed effects. The specification is as follows:

$$\log(\text{energyShare}_{ist}) = \beta_0 + \beta_1 \log(\text{income}_i) + X_{it} + \gamma_t + \gamma_s + \varepsilon_{ist} \tag{31}$$

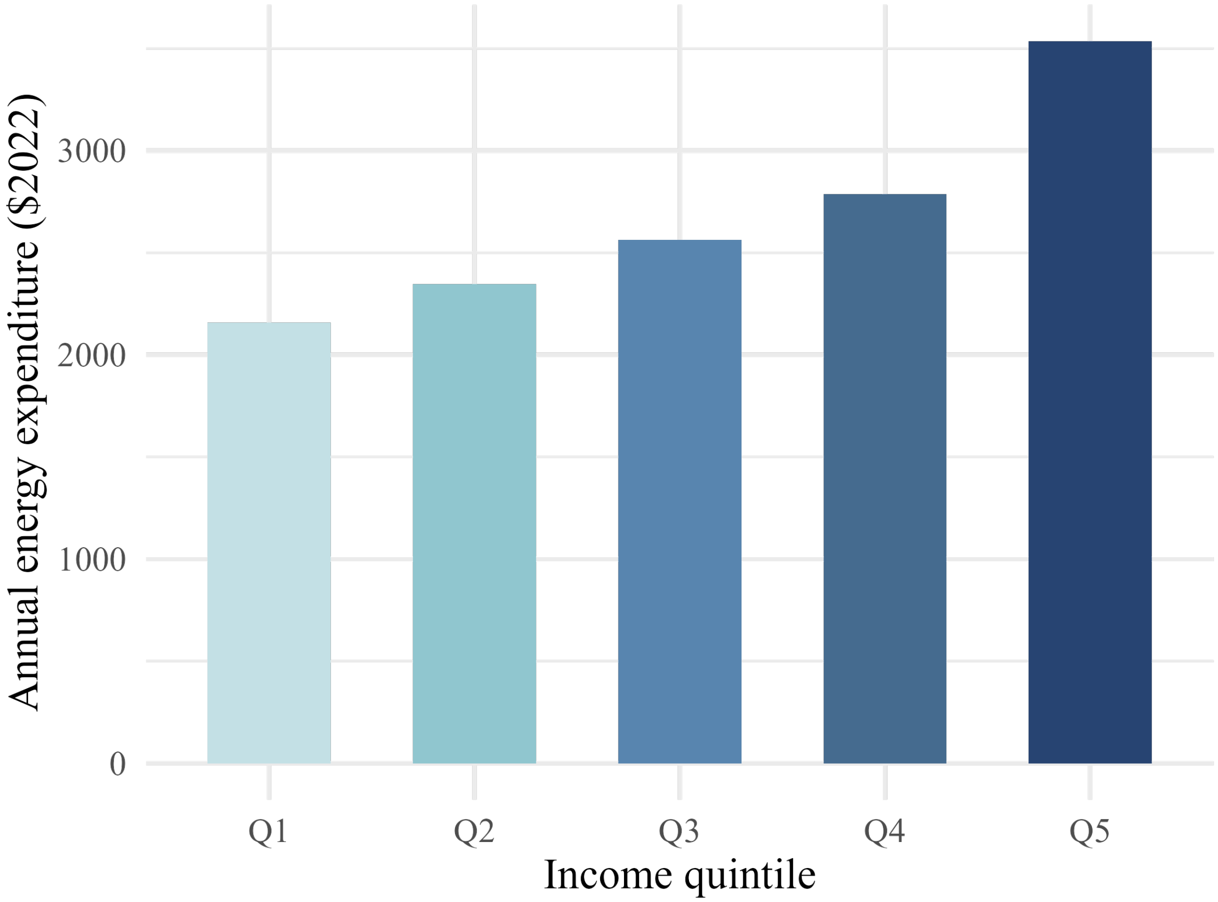
Here, energyShare_{ist} is the ratio of household i's energy expenditure to total expenditure in state s and year t, and income_i denotes the lifetime income measure described earlier. The control vector X_{it} includes climate controls (heating and cooling degree days), housing characteristics, household size, and demographics, as specified in the previous subsection. The sample is restricted to households using either electricity or gas as their primary heating source.

Figure C1. Energy Expenditure shares by income quintile



Notes: The figure shows the share of total expenditure devoted to energy (electricity and gas) across income quintiles. Lower-income households spend a much larger fraction of their budgets on energy than higher-income households, consistent with energy being a necessity good. Data are from the PSID.

Figure C2. Energy expenditures by income quintile (levels)



Notes: This figure shows the average annual household energy expenditures (in dollars), by income quintile. Higher-income households spend more in absolute terms, but energy represents a smaller portion of their total budgets, reflecting declining expenditure shares with income. Data are from the PSID.

The coefficient of interest, β_1, captures the elasticity of energy expenditure share with respect to income. A negative value indicates that higher-income households spend a smaller proportion of their budget on energy, consistent with non-homothetic preferences. Table 6 reports results from three specifications: (1) a baseline model without controls or fixed effects; (2) a specification with controls only; and (3) a fully saturated model including both controls and state and year fixed effects.

In all three models, β_1 is negative and highly significant. In the fully specified model, the estimate implies that a 1% increase in income is associated with an approximate 0.39% reduction in the energy expenditure share. These findings robustly support the view that energy is a necessity good, and that energy consumption is non-homothetic with respect to income.

Table 6: Income and Energy Expenditure Share

	(1) Baseline	(2) + controls	(3) + year/state FE
log income	-0.289^{***}	-0.311^{***}	-0.288^{***}
	(0.003)	(0.004)	(0.012)
Controls	No	Yes	Yes
Year FE	No	No	Yes
State FE	No	No	Yes
Observations	41,686	36,764	36,764
R^2	0.15	0.22	0.30

Notes: Coefficients are from linear regressions. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is the log of energy expenditure share. Controls and fixed effects are added sequentially across specifications. Controls include heating and cooling degree-days (base 65°F/18°C), age (squared), house tenure, family size (squared) and house type.

Appendix D: Computational Appendix

This appendix summarizes the numerical solution method and key computational parameters.

D.1. Algorithm Overview

The model is solved by value-function iteration with logit switching and Howard improvement. The essential steps are:

1. Discretize the state space $s = (a, z, k, \gamma)$. Idiosyncratic productivity z follows an AR(1) process discretized via Rouwenhorst, while γ follows a Markov chain.

2. Given value function $V^{(n)}$, compute expected continuation value and update via one-dimensional maximization over c:

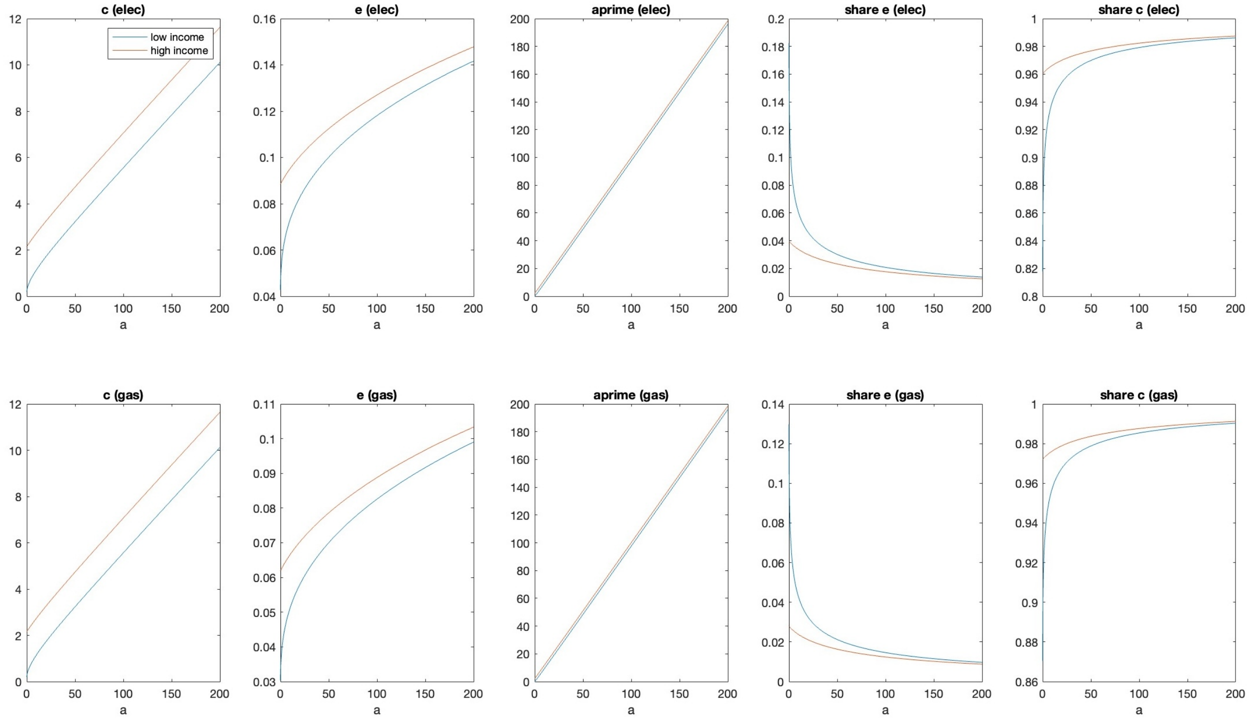
    - Golden-section search for “keep” and “switch” branches
    - Log-sum-exp aggregation for discrete technology choice

3. Every 15 iterations, apply Howard policy improvement holding policies fixed. Convergence: $\|V^{(n)} - V^{(n-1)}\|_2 < 10^{-7}$.

4. Simulate $N = 10{,}000$ households for $T = 5{,}000$ periods (discarding 2,000 burn-in).

Figure D1 shows the resulting optimal policy functions.

Figure D1. Sampled Optimal Policy Functions



Notes: Sampled policy functions for non-energy consumption, energy consumption, savings, for electricity users (top) and gas users (bottom), for high and low-income households, shown here as a function of assets. The two rightmost columns show the decreasing energy expenditure share with income and the implied increasing non-energy expenditure share.