# COMMUTING, HOME UTILITIES, AND PRODUCTION: THE DISTRIBUTIONAL EFFECTS OF ENERGY PRICE SHOCKS*

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**ABSTRACT**

Energy price shocks are large and persistent relative to other price shocks. How do these shocks affect households in different income groups? Using the Consumer Expenditure Survey (CEX), I document a negative relationship between household income and the expenditure share on energy for both commuting and residential utilities. Households in the lowest income quintile spend 12.5% of their budget on energy, while the highest spend 7.8%. To quantify the welfare effects of an energy price shock across income groups, I develop a heterogeneous-agent incomplete market model featuring non-homothetic consumption preferences, costs of commuting to work, and energy as a factor of production for non-energy goods, taking energy price as exogenous. A calibrated version of the model successfully reproduces many salient features of the United States data, including the cross-sectional distribution of employment, income, wealth, and expenditure shares on energy consumption for both commuting and residential utilities. An energy price shock in the model unevenly impacts households in different income groups. Specifically, a one-standard-deviation inflationary shock results in four times greater welfare losses for those in the lowest income quintile than those of the highest quintile on impact. The paper also shows that while work-from-home opportunities exacerbate inequality, targeted transfers help to mitigate it.

*Keywords*: Energy Price Shock; Inequality; Labor Supply; Commuting Cost; Non-Homothetic Consumption Preference.

*JEL Codes*: D63, E21, E30, Q43.

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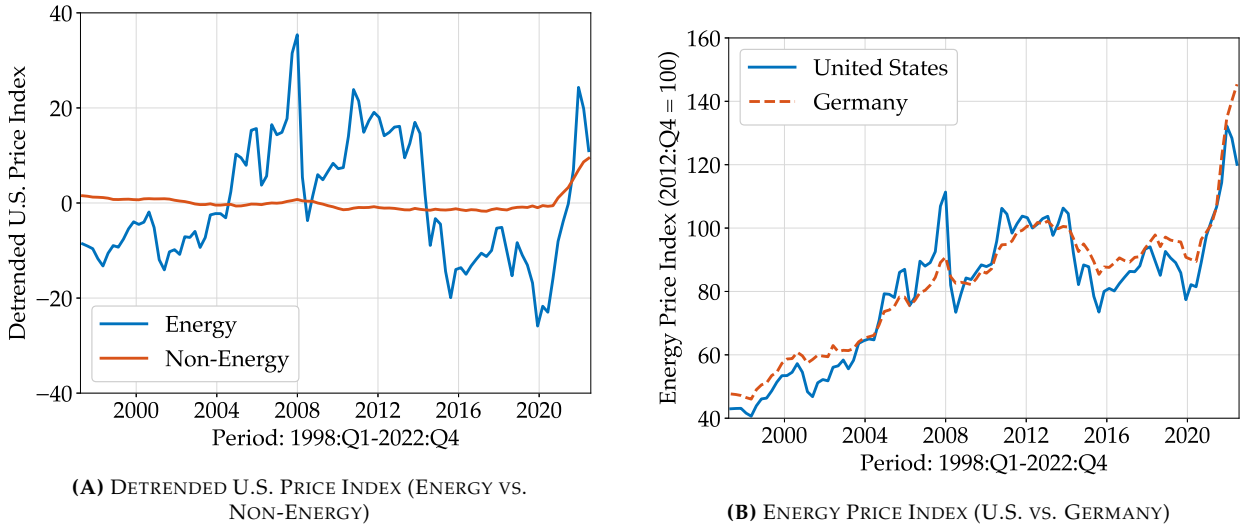
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## 1. Introduction

Typically, energy prices experience sharp and sustained fluctuations compared to the prices of other goods and services (see Figure 1 Panel A). These fluctuations are common across economies worldwide, including large energy-producing countries like the United States and major energy-importing countries like Germany (see Figure 1 Panel B), stemming from common factors such as wars (e.g., political unrest in the Middle East or the recent Russian invasion of Ukraine), energy plant accidents, or initiatives aimed at controlling energy use for environmental concerns. Fluctuations in energy prices have greater significance for an economy than other prices due to two main facts: (i) energy is used both by firms and households, and (ii) the demand for energy is inelastic. A primary concern for policymakers has been the potential negative impact of high energy prices on consumer demand, which is typically addressed with transfer programs or price regulations. To effectively design these policies, it is crucial to understand the potential distributional consequences of both energy price shocks and the policies initiated in response. Despite the extensive literature studying the macroeconomic impacts of energy price shocks, there is less work on the distributional effects. Moreover, a careful evaluation of energy-related policies requires a comprehensive framework incorporating different uses of energy.

In this paper, I study the distributional effects of an energy price shock by developing a unified framework of energy use in residential utilities (such as heating, cooling, and cooking), commuting to work, and production.[1] In doing so, I make four key contributions. First, using the Consumer Expenditure Survey (CEX), I document a robust negative relationship between income and household expenditure share on energy both for residential utilities and commuting. Second, I develop a heterogenous-agent incomplete market model building on Bewley-Imrohoroğlu-Huggett-Aiyagari, with an exogenous energy price, featuring non-homothetic consumption preferences, extensive and intensive margin labor supply choices, costs of commuting to work, and a production sector that produces

1. Energy price refers to the price index that accounts for all types of final-use energy, which households and firms use directly, such as gasoline, piped gas, and electricity.




**(A)** DETRENDED U.S. PRICE INDEX (ENERGY VS. NON-ENERGY)

**(B)** ENERGY PRICE INDEX (U.S. VS. GERMANY)

**FIGURE 1**
COMPARISON IN FLUCTUATIONS OF ENERGY VS. NON-ENERGY PRICE INDEX FOR THE U.S. AND ENERGY PRICE INDEX FOR THE U.S. VS. GERMANY

*Note.* Panel (A) plots the detrended Consumer Price Index (CPI) for energy and non-energy in the U.S. (BEA CPI-U: SA0E & SA0LE). Panel (B) plots the CPI for energy in the U.S. and the Harmonized Index of Consumer Prices (HICP) for energy in Germany (Eurostat: EI_CPHI_M: CP-HIE).

non-energy goods using energy as a factor of production. Third, in calibrating the model, I provide new estimates for the household demand system that includes energy in the consumption basket. Using the calibrated model, I find that a one-standard-deviation inflationary energy price shock—equivalent to a 5% increase in the relative price of energy on impact—results in welfare losses for households in the lowest income quintile four times as large as those in the highest income quintile on impact ($-0.39\%$ vs. $-0.11\%$ in terms of consumption). Finally, in a set of counterfactual exercises, I analyze the influence of work-from-home (WFH) opportunities and targeted transfer programs on shock impacts. I find that only households allowed to work from home benefit from such options. In contrast, targeted transfers to low-income households benefit the broader income distribution.

In the model, all households consume a combination of energy and non-energy goods from which they derive utility. They also value leisure and can decide whether to work, and if so, the number of hours. Households that choose to work consume additional energy for commuting, thereby incurring commuting costs. These commuting costs depend on household earnings and only appear as an expense in household budget constraints. Households

finance their consumption from disposable income and can borrow or save to insure themselves against productivity shock. Households earn labor and asset income, pay taxes, and receive transfers that ensure a minimum level of consumption. In the absence of these transfers, contrary to the data, all households with zero wealth would necessarily choose to work to finance their consumption regardless of their productivity levels.

On the production side, a representative firm produces non-energy goods using labor, capital, and energy. To capture the low short-run elasticity of substitution between energy and non-energy factor inputs, as documented in the literature, these inputs are combined in fixed proportions (see, e.g., Casey, 2023). Motivated by the literature and the fact that the energy price follows the world price, energy is considered entirely imported at an exogenous price (see, e.g., Kim and Loungani, 1992; Alpanda and Peralta-Alva, 2010). The output from the production sector is devoted to household non-energy consumption and exports to balance trade for the economy's energy imports.

An energy price shock directly impacts the composition of household energy and non-energy consumption. Due to the inelastic demand for household energy consumption and the dependency of labor supply on commuting costs, such a shock directly impacts household budget constraints. For instance, with an increase in energy price, household real income falls, compelling them to increase their labor supply. However, higher labor supply increases commuting costs, leaving households with limited resources for residential energy and non-energy consumption. Hence, a trade-off between earnings and commuting costs influences household labor supply decisions. In addition, the energy price shock indirectly impacts household decisions by influencing their earnings and asset return through changes in firms' demand for different factors and their respective prices.

I calibrate the model to U.S. data. Specifically, I use the CEX data to estimate the demand system derived from my model and obtain the elasticity of substitution between residential energy and non-energy consumption, along with the parameters governing the expenditure elasticities of demand. Notably, the expenditure elasticity of demand for energy is roughly half that of non-energy, which is robust to reduced-form estimates I obtain in a

validation exercise. I also use the CEX data to calibrate parameters related to households' energy use in commuting. The commuting cost is increasing in household income, which is consistent with the empirical evidence (see, e.g., Ready, Roussanov, and Zurowska, 2019; Kimbrough, 2019). The calibrated model successfully reproduces many salient features of the U.S. data, including the cross-sectional distributions of employment rate, earnings, wealth, as well as expenditure shares on both residential and commuting energy.

I use the calibrated model to analyze the distributional effects of an energy price shock. Specifically, I quantify the impact of a one-standard-deviation inflationary energy price shock (equivalent to a 5% increase in the relative price of energy). The model predicts that such an increase in energy price leads to higher household consumption costs, reducing real income and causing a rise in labor supply. This response in labor supply varies across the income and wealth distributions due to the varying marginal utility of consumption. Particularly, low-income households, who have no savings to insure themselves against the shock, rely on increasing their labor supply to smooth consumption. Nevertheless, the increase in labor supply generates additional welfare losses for households, as higher commuting costs limit their other consumption (i.e., residential energy and non-energy), and reduced leisure increases disutility. The quantitative analysis finds that the energy price shock leads to disproportionate welfare losses across income groups, with the lowest income quintile bearing a burden more than four times as heavy as that of the highest income quintile on impact ($-0.39\%$ vs. $-0.11\%$ in terms of consumption).

Next, I examine how WFH opportunities influence the impact of an inflationary energy price shock. Since the COVID-19 pandemic, WFH has become commonplace. It significantly lowers commuting costs, allowing households to reallocate their resources to other consumption or investment. Nonetheless, the option of working from home is notably higher in high-skilled occupations, thus predominantly favoring high-skilled households (see, e.g., Bick, Blandin, and Mertens, 2023; Barrero, Bloom, and Davis, 2023). Motivated by this fact, in my model, I allow households in the top earnings quintile to WFH by exoge-

nously reducing their commuting energy consumption.[2] This adjustment results in welfare gains for those households even after an inflationary energy price shock. In contrast, other households still experience similar welfare losses to the no WFH case, exacerbating the overall welfare disparity in the economy.

Lastly, motivated by the U.S. federal energy assistance program—the Low Income Home Energy Assistance Program (LIHEAP)—I explore the influence of targeted transfers on the impact of an inflationary energy price shock. In doing so, I provide a lump-sum transfer to households in the lowest income quintile in my model following an inflationary energy price shock. This transfer significantly improves the welfare of the targeted group. In addition, by providing insurance to low-income households, the transfer reduces uncertainty in the incomplete market setting, thereby improving welfare across the income distribution.

**Outline.** The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents empirical evidence that motivates the key features of the quantitative model. Section 4 outlines the model and defines the equilibrium. Section 5 describes the calibration strategies. Section 6 assesses the model's ability to reproduce empirical statistics of interest. Section 7 contains the quantitative analysis. Section 8 presents concluding remarks. Appendices contain additional details on the data and the model.

## 2. Relevant Literature

This paper relates to the macroeconomic literature that studies the effects of energy price shocks. A substantial number of papers in this literature empirically study the macroeconomic implications of various types of energy price shocks, with a prominent focus on oil price shocks (see, e.g., Hamilton, 1983, 2003; Barsky and Kilian, 2004; Kilian, 2008, 2009; Edelstein and Kilian, 2009; Baumeister and Kilian, 2014; Känzig, 2021). On the other hand, Kim and Loungani (1992), Dhawan and Jeske (2008), Dhawan, Jeske, and Silos (2010), and

2. In my model, higher productivity leads to higher earnings. Hence, high-earning households are considered to be high-skilled.

Schwark (2014), among others, study the effects of energy price shocks on economic aggregates in quantitative macroeconomic models.

The recent surge in energy price leads several papers to study the distributional effects of energy price shocks. Del Canto, Grigsby, Qian, and Walsh (2023) empirically analyze the first-order impacts of oil price shocks on households in different demographic groups. Closest to this paper, Kuhn, Kehrig, and Ziebarth (2021) and Pieroni (2023) study the distributional effects of energy-related shocks in quantitative models.[3] This paper distinguishes itself by incorporating a more flexible household demand system, commuting costs, labor supply choice at the extensive margin, capital accumulation, and a production function consistent with the data.[4] Incorporating these features not only provides more precise estimates of shock impacts but also makes the model suitable for analyzing a wider range of policy rules than the existing models in the literature.

This paper builds on recent quantitative macroeconomic studies that analyze the effects of aggregate shocks in heterogeneous-agent incomplete market models (e.g., Boppart, Krusell, and Mitman, 2018; de Ferra, Mitman, and Romei, 2020; Auclert, Rognlie, Souchier, and Straub, 2021; Guerrieri, Lorenzoni, Straub, and Werning, 2022). Unlike these papers, it analyzes the impact of an energy price shock in a unified framework of energy use in residential utilities, commuting to work, and production. Consequently, the model incorporates energy in both consumption and production.

The paper also relates to the empirical literature on elasticities of energy demand (e.g., Havranek and Kokes, 2015; Heindl and Schulte, 2017; Labandeira, Labeaga, and López-Otero, 2017). Particularly, Labandeira, Labeaga, and López-Otero (2017) conduct an extensive meta-analysis on the price elasticities of energy, distinguishing between various energy

3. Pieroni (2023) studies the impacts of energy supply reduction in the Euro Area using a Heterogeneous Agents New Keynesian (HANK) model. Kuhn, Kehrig, and Ziebarth (2021) use a similar model with flexible prices to study the effects of a gasoline price shock on U.S. households.

4. To incorporate non-homotheticity in household consumption, Pieroni (2023) use Stone-Geary preferences, and Kuhn, Kehrig, and Ziebarth (2021) introduce idyosyncratic gas consumption independent of household income. While Stone-Geary preferences result in Engel curves that level off quickly as income grows, the demand system of my paper preserves non-homotheticity for all income levels. On the production side, while both papers omit capital in production, the Cobb-Douglas production function in Kuhn, Kehrig, and Ziebarth (2021) is inconsistent with the data (Casey, 2023).

types, consumer demographics, geographical regions, data types, and estimation methods. In another meta-analysis, Havranek and Kokes (2015) focus on the income elasticity of energy demand. My paper contributes to this literature by estimating the demand system derived from the non-homothetic constant elasticity of substitution (CES) consumption preferences. It provides new estimates for the elasticity of substitution between residential energy and non-energy consumption, along with their respective expenditure elasticities of demand. Notably, in my model, expenditure elasticities vary across households and depend on the composition of household consumption expenditures.

Finally, the recent surge in energy price leads a growing number of studies exploring their implications for energy-related policies. In an open economy HANK model, Auclert, Monnery, Rognlie, and Straub (2023) shows that after an energy price shock, monetary tightening is costly but brings positive externalities for other energy importers. Conversely, fiscal policies can mitigate the impact of energy price shocks but impose negative externalities on other countries. Langot, Malmberg, Tripier, and Hairault (2023) explore policies like wage indexation to prices and targeted redistribution in the context of France. I contribute to this literature by investigating the distributional impacts of implementing a targeted transfer and introducing WFH opportunities following an energy price shock.

## 3. Empirical Evidence

### *3.1. Energy Consumption of Households and Firms*

**Data.** I use data from the U.S. Energy Information Administration (EIA), which provides information on final-use energy consumption and expenditures, categorized into four broad sectors: residential, commercial, industrial, and transportation.[5] For my analysis, I reclassify these sectors into two categories: household and firm energy consumption. Household energy consumption includes residential and a fraction of transportation energy consumption, specifically energy consumed as fuel for personal vehicles. Firm energy consumption

5. Final-use energy refers to the energy commodities that are directly consumed by households and firms, such as electricity, gasoline, and piped gas.

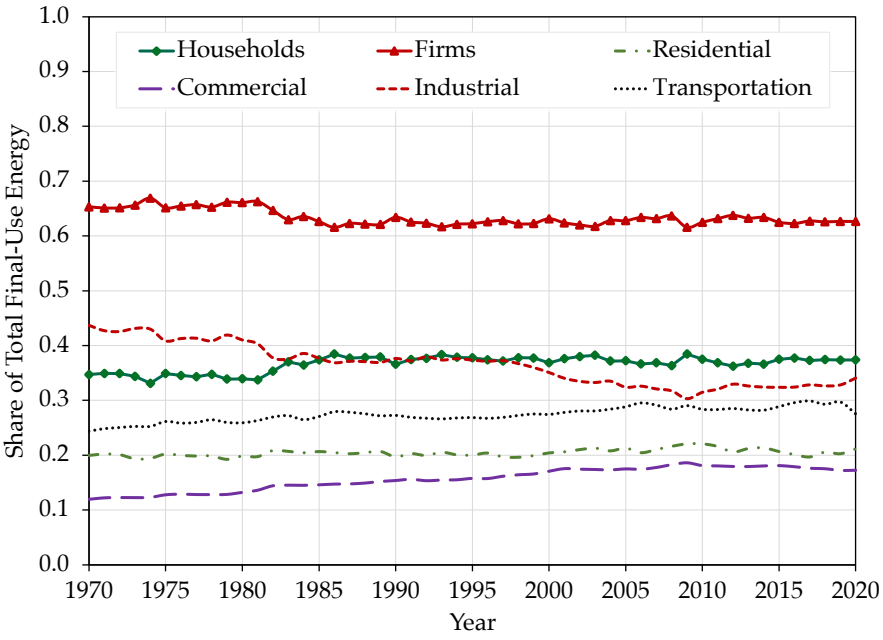



**FIGURE 2**
PATTERNS OF ENERGY CONSUMPTION

*Note.* The figure plots historical patterns of energy consumption in the U.S., represented as a share of total final-use energy, measured in British Thermal Units (BTU).

includes the remaining energy consumption in the transportation sector, as well as energy consumption in the industrial and commercial sectors.

I estimate household energy consumption as fuel for personal vehicles from the total transportation energy consumption in three steps. First, I derive household expenditures on motor fuel by subtracting the expenditures on residential energy consumption from the total household energy expenditures reported in the National Income and Product Account (NIPA).[6] Second, I calculate the price of energy in the transportation sector using consumption and expenditure data from the EIA. Finally, I obtain energy consumption as fuel for personal vehicles using household expenditures on this category and its price.

**Fact.** Figure 2 plots the patterns of energy consumption across different sectors in the U.S. from 1970 to 2020. Over the last fifty years, the shares of energy consumption in the residential, commercial, industrial, and transportation sectors have remained relatively constant,

6. Table 2.3.5. Personal Consumption Expenditures by Major Type of Product.

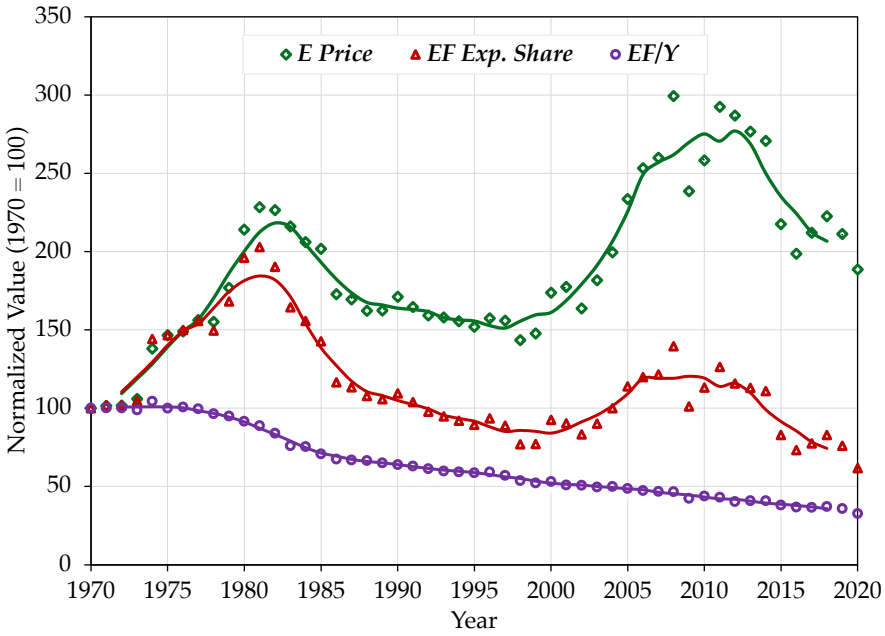



**FIGURE 3**
ENERGY INTENSITY OF OUTPUT

*Note.* The figure shows the firms' energy expenditure share ($E_F$ *exp. share*), the (final-use) energy intensity of output ($E_F/Y$), and the average real energy price ($\tilde{p}_E$) in the U.S. from 1970 to 2020. These plotted objects are related through the identity $E_F$ *exp. share* $= \tilde{p}_E \cdot (E_F/Y)$ . The markers represent data points normalized to 1970 values, and the lines show 5-year moving averages.

except for a slight decrease in the industrial sector and a slight increase in the commercial sector. On average, the industrial sector accounts for roughly one-third of total energy consumption, followed by the transportation, residential, and commercial sectors. About half of the energy in the transportation sector is directly consumed by households as fuel for personal vehicles, with the remaining fraction used to provide transportation services.

Overall, Figure 2 indicates that approximately two-thirds of the total energy is used as an input to produce non-energy goods and services. Consequently, considering energy as an input for producing non-energy goods and services is non-trivial for my study.

### *3.2. Response of Energy Demand in Production to Its Price Fluctuations*

Figure 3 summarizes evidence on the energy demand in the production sector. It plots the firms' expenditure share of energy ($E_F$ *exp. share*), the energy intensity of output ($E_F/Y$), and the average real price of final-use energy ($\tilde{p}_E$) in the U.S. for the period 1970 to 2020.

The figure shows that while the expenditure share reacts to short-run price fluctuations, the energy intensity of output does not, suggesting that it is difficult to substitute between energy and non-energy factor inputs in the short run.[7] In contrast, the figure reveals a reduction in energy intensity in the long run. The decline in energy intensity, in the long-run, can result from technical change or sectoral reallocation (Sue Wing, 2008).[8]

### *3.3. Heterogeneity in Expenditure Share on Energy Across Households*

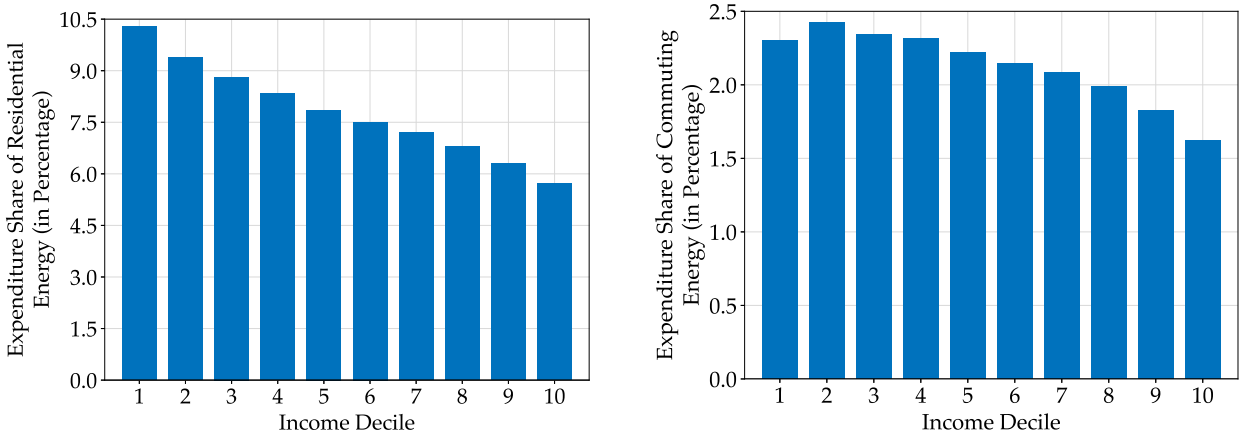
**Data.** I analyze variations in household energy consumption expenditures across income groups using quarterly household-level consumption expenditure data from the CEX. It is a nationally representative survey conducted by the Bureau of Labor Statistics (BLS) that reports data on income, expenditures, and demographic characteristics of U.S. households. The comprehensive coverage of household consumption expenditures in CEX makes it particularly suited for my analysis.

I use data spanning from 1999 to 2013, restricting the sample to households whose heads are aged between 25 and 64, participated in at least four interviews, and are complete income reporters.[9] The dataset is constructed following the methodology of Aguiar and Bils (2015), which closely aligns with Krueger and Perri (2006) and Heathcote, Perri, and Violante (2010). The CEX includes household expenditures on hundreds of different items. I categorize these items in household consumption baskets into three broad groups: (i) *commuting energy*, which includes energy commodities consumed as fuel for personal vehicles

7. Hassler, Krusell, and Olovsson (2021) estimate the short-run elasticity of substitution between energy and non-energy inputs using maximum likelihood and find it to be close to zero.

8. Decomposition analyses suggest that improvements in intra-sectoral efficiency, rather than sectoral reallocation, have been the principal driver of falling energy intensity over this period (see, e.g., Metcalf, 2008; Sue Wing, 2008). Several studies in energy crisis and climate policy literature reveal a significant shift in energy prices and energy efficiency improvements coinciding with the energy crisis of the early 1970s (e.g., Baumeister and Kilian, 2016; Fried, 2018; Hassler et al., 2021). Prior to the crisis, energy prices were either constant or decreasing and decomposition analyses suggest that sectoral reallocation was the primary factor driving the reduction in energy intensity for that period (Sue Wing, 2008).

9. I choose 2013 as the final year of my CEX sample due to the termination of the variable that represents complete income information. On the other hand, I choose 1999 as the starting year to maintain consistency with my quantitative analysis. To estimate parameters related to household consumption preferences, I use a 'Hausman' relative-price instrument, which is constructed by combining CEX expenditure data with disaggregated regional quarterly price series from the BLS's Urban CPI (CPI-U), which started in 1999. However, it is worth noting that extending the sample period in both directions yields very similar results.




**(A)** DISTRIBUTION OF EXPENDITURE SHARE ON RESIDENTIAL ENERGY

**(B)** DISTRIBUTION OF EXPENDITURE SHARE ON COMMUTING ENERGY

**FIGURE 4**
DISTRIBUTIONS OF HOUSEHOLD EXPENDITURE SHARE ON RESIDENTIAL AND COMMUTING ENERGY

*Note.* The figure shows the distributions of household expenditure shares for residential (Panel A) and commuting (Panel B) energy using the CEX data. Commuting energy shares are conditional on employment. However, income groups remain unconditional for consistency.

for commuting to work; (ii) *residential energy*, which includes energy commodities used for purposes other than commuting to work; and (iii) *non-energy*.

The CEX does not report direct information on energy consumption for commuting to work. However, it reports household expenditures on gasoline and motor oil, including specific spending on these items for long drives and vacations. To extract energy expenditures related to commuting to work, first, I subtract household energy expenditures for long drives and vacations from their total gasoline and motor oil expenditures. Next, I regress the log of the resulting variable on log after-tax income, log household total expenditure, quadratic time trends, and a binary dummy variable indicating households with at least one earner. I then use the coefficient of the dummy variable to obtain household energy expenditure for commuting to work. The remaining gasoline and motor oil expenditures are merged with the residential energy expenditures.

**Fact.** Figure 4 plots household expenditure shares on residential and commuting energy by income deciles. The plotted moments are time-averaged over the sample period (i.e., 1999-2013). The figure reveals a clear negative correlation between household expenditure

shares on energy and income levels. Specifically, for the lowest income decile, the expenditure share on residential energy is 4.5 percentage points higher than that of the highest income decile. Compared to the expenditure share on residential energy, the expenditure share on commuting energy experiences a slower gradual decline over income deciles. The difference in expenditure share on commuting energy between the lowest and highest income decile is approximately 0.80 percentage points. This negative relationship between expenditure shares on energy (both residential and commuting) and income remains consistent across various subgroups, including age, family size, education level, and region, confirming that the relation is not a compositional effect but a direct and robust association.

Overall, Figure 4 indicates that the composition of household energy and non-energy consumption varies across income groups. In other words, household preferences over energy and non-energy consumption goods are non-homothetic.

The empirical evidence presented in this section motivates the key features of the quantitative model developed in the following section.

## 4. Quantitative Model

Time is discrete and continues forever, indexed by $t = 1, 2, 3, \cdots, \infty$. The economy is populated by a continuum of infinitely-lived households with unit measure. Households differ according to their labor efficiency $z_t \in \mathcal{Z}$. Specifically, each household is endowed with one unit of time per period, yielding $z_t$ units of efficiency labor input, where $z_t$ is independent and identically distributed (i.i.d.) across households and follows a stochastic process. There is no direct insurance against idiosyncratic risks. However, households can save and borrow subject to a borrowing constraint.

In the economy, energy commodities serve multiple roles, such as household consumption and production input. These energy commodities are entirely imported at an exogenous price $\tilde{p}_{Et}$ as in Alpanda and Peralta-Alva (2010), among others.[10]

10. This assumption is also supported by the fact that energy price follows the world price.

### 4.1. *Technology*

A representative firm operates using capital, labor, and energy as factor inputs. To capture the low short-run elasticity of substitution between energy and non-energy inputs, as observed in the literature (see, e.g., Hassler, Krusell, and Olovsson, 2021), I consider a constant returns to scale (CRS) Leontief production technology:

$$Y_t = \min \left[ K_t^{\alpha} {L_t}^{1-\alpha}, \kappa A_{Et} E_{Ft} \right], \tag{1}$$

$$\text{s.t. } \kappa A_{Et} E_{Ft} \leq K_t^{\alpha} {L_t}^{1-\alpha}, \tag{2}$$

where $K_t$ is the capital input, $L_t$ is the labor input measured in efficiency units, $E_{Ft}$ is the energy input, $\alpha \in (0,1)$ is the output elasticity of capital, and $\kappa A_{Et}$ represents the energy efficiency of the production technology.[11] $A_{Et}$ captures energy-efficient technological progress and $\kappa > 0$ is the base energy efficiency level in the absence of technological progress.[12] The evolution of the aggregate capital stock is given by

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{3}$$

where $I_t$ is gross investment and $\delta$ is the capital depreciation rate.

The Cobb-Douglas composite of capital and labor in equation (1) measures the maximum level of output and the production process requires energy to operate. The notion of maximum output is captured by constraint in equation (2). In each period, a fraction of the output is devoted to meeting household non-energy consumption, while the remaining fraction is exported to balance trade for the economy's energy imports.

11. Using a capital-labor composite is a more attractive nesting option than alternatives. Specifically, a structure where either capital or labor forms a composite with energy would imply significant changes in the capital or labor income shares in response to energy shocks. However, such changes are not observed in the data (see, e.g., Hassler, Krusell, and Olovsson, 2021).

12. Energy-efficient technological progress can address the long-run decline in energy intensity in production, as shown in Figure 3.

### 4.2. *Preferences*

Households have preferences over a basket of consumption goods, $\boldsymbol{x}$, and leisure, $1-h$. The period utility function is separable over consumption and labor supply: $u(\boldsymbol{x}, h) = u_x(\boldsymbol{x}) - u_h(h)$, where $u_x$ is strictly increasing, concave, and twice continuously differentiable in its arguments, representing the utility from energy ($E_R$) and non-energy ($C$) consumption goods. Energy in the utility function only refers to residential use of energy (i.e., energy use other than commuting to work). Households also consume energy to commute to work, which provides no direct utility. The other part of the utility function $u_h$ is strictly increasing, convex, and twice continuously differentiable in its argument, capturing the disutility from work. Let $\beta \in (0,1)$ denotes the time discount factor, then the household's lifetime utility is given by

$$\mathcal{U}_0 = \mathbb{E}_0 \left[ \sum_{t=0}^{\infty} \beta^t \big( u_{xt}(\boldsymbol{x}_t) - u_{ht}(h_t) \big) \right], \tag{4}$$

where $\mathbb{E}_0$ is the expectation operator conditional on the information available at time $t = 0$.

### 4.3. *Budget Constraint*

Each period, a household's pre-government income comes from two sources: (i) earnings, $z_t w_t h_t$, where $w_t$ represents the wage per efficiency unit of labor hour; and (ii) asset income, $r_t a_t$, for $a_t > 0$, where $r_t$ denotes the rate of return of the asset. The household pays a fraction of its pre-government income as taxes and receives transfers. With its disposable income (i.e., total income minus taxes plus transfers), the household decides its consumption expenditures and whether to save or borrow, subject to a borrowing constraint that must not exceed $\underline{a}$, where $\underline{a} \leq 0$. Hence, the household's budget constraint is given by

$$\begin{aligned} p_{Et}\Big(E_{Rt} + E_{Tt}\left(z_t w_t h_t\right) \cdot \mathbb{1}_{\{h_t > 0\}}\Big) + C_t + a_{t+1} = \\ z_t w_t h_t - \mathcal{T}\left(z_t w_t h_t\right) + (1 + (1-\tau^a) r_t) a_t + T(a_t) \cdot \mathbb{1}_{\{h_{it}=0\}}, \end{aligned} \tag{5}$$

$$a_{t+1} \geq \underline{a}, \text{ with } \underline{a} \leq 0, \tag{6}$$

where the price of the non-energy consumption is normalized to 1, and $p_{Et}$ denotes the relative price of energy. $E_{Tt}(z_t w_t h_t)$ represents the household's energy use for commuting. The indicator function, $\mathbb{1}_{\{h_t>0\}}$, is equal to one if $h_t > 0$ and zero otherwise, implying that commuting costs are applicable only to households with non-zero working hours. $\mathcal{T}(z_t w_t h_t)$ is the net tax on earnings, calculated using a parametric class of tax and transfer functions $\mathcal{T}(\cdot)$. $(1-\tau^a)r_t$ is the after-tax rate of return, where $\tau^a$ is a flat-rate tax on asset income. The last term $T(a_t)$ represents the means-tested transfers, and the indicator function, $\mathbb{1}_{\{h_t=0\}}$, equals one if the household is non-employed ($h_t = 0$) and zero if employed ($h_t > 0$). This transfer is determined as follows:

$$T(a_t) = \max\left\{0, \bar{e} - (1 + (1-\tau^a)r_t)\, a_t \cdot \mathbb{1}_{\{a_t>0\}}\right\}, \tag{7}$$

where $\bar{e}$ denotes the maximum level of lump-sum transfer that a non-employed household can receive. The indicator function, $\mathbb{1}_{\{a_t>0\}}$, equals zero if $a_t \leq 0$ and one if $a_t > 0$. Specifically, Equation (7) suggests that non-employed households receive $\bar{e}$ net of what they could afford by selling off their wealth.

### *4.4. Government*

The government collects taxes on assets and earnings and disburses transfers to households. To ensure a minimum level of consumption expenditure for non-employed households, it operates a means-tested transfer program. Without this transfer program, households with zero wealth would be compelled to work to finance their consumption, irrespective of their productivity level.

The government budget is balanced period-by-period, with government spending (i.e., government consumption, $G_t$, and transfers) equaling tax revenues in each period.

### *4.5. Household Problem*

I formulate the household problem in recursive form and use primes to denote next-period variables. The value function of a household with asset possession $a$ and productivity level $z$ at time $t$ is $V_t(a,z) = \max\{V_t^E(a,z), V_t^U(a,z)\}$, where $V_t^E(a,z)$ and $V_t^U(a,z)$ are the value

functions conditional on working and not working, respectively. The household decides to work if $V_t^E(a,z) > V_t^U(a,z)$ and decides not to work if otherwise.

If the household decides to work, its value function is given by:

$$\begin{aligned} V_t^E(a,z) = \max_{\{\boldsymbol{x}_t, h_t, a'\}} & \left\{ u_{xt}(\boldsymbol{x}_t) - u_{ht}(h_t) + \beta \mathbb{E}_t \left[ V(a', z') | z \right] \right\}, \\ \text{s.t.} \quad & P_t \boldsymbol{x}_t + p_{Et} E_{Tt}(z w_t h_t) + a' = z w_t h_t - \mathcal{T}(z w_t h_t) + (1 + (1 - \tau^a) r_t) a; \\ & a' \geq \underline{a}; \\ & \boldsymbol{x}_t \geq 0, \;\; h_t \in [0,1], \end{aligned}$$

where $P_t$ is the price index of the household's consumption basket, $\boldsymbol{x}_t$.

On the other hand, if the household decides not to work, its value function is given by:

$$\begin{aligned} V_t^U(a,z) = \max_{\{\boldsymbol{x}_t, a'\}} & \left\{ u_{xt}(\boldsymbol{x}_t) + \beta \mathbb{E}_t \left[ V(a', z') | z \right] \right\}, \\ \text{s.t.} \quad & P_t \boldsymbol{x}_t + a' = (1 + (1 - \tau^a) r_t) a + T(a); \\ & a' \geq \underline{a}; \\ & \boldsymbol{x}_t \geq 0. \end{aligned}$$

### *4.6. Firm Problem*

A representative firm at time $t$ rents capital at rate $R_t \equiv r_t + \delta$, hires labor at wage $w_t$, and purchases energy at price $p_{Et}$ to carry on production and maximize profits:

$$\max_{\{L_t, E_{F_t}, K_t\}} \Pi_t \equiv Y_t - R_t K_t - w_t L_t - p_{Et} E_{F_t}, \tag{8}$$

subject to the production technology in equation (1). The production takes place in a perfectly competitive environment, and the output price is normalized to one. The price of the energy input is exogenous, while the rental rate of capital and wage equal their respective marginal products:

$$R_t = \alpha \left(1 - \frac{p_{Et}}{\kappa A_{Et}}\right) \left(\frac{K_t}{L_t}\right)^{\alpha - 1}; \tag{9}$$

$$w_t = (1 - \alpha) \left(1 - \frac{p_{Et}}{\kappa A_{Et}}\right) \left(\frac{K_t}{L_t}\right)^{\alpha}. \tag{10}$$

Equations (9) and (10) show that the rental rate and the wage are functions of the energy price and energy efficiency of production technology, implying that a change in the energy price or energy efficiency can directly impact both of the non-energy factor prices.

### *4.7. Equilibrium*

I consider the economy to be initially in a steady state without aggregate uncertainty and unexpectedly encounter an exogenous shock to the energy price. Following the shock, households have perfect foresight over the future sequence of the energy price.

The state space is denoted as $\mathcal{S} \equiv \mathcal{A} \times \mathcal{Z}$ and households are indexed by $s \equiv (a, z) \in \mathcal{S}$. Let $\Sigma_{\mathcal{S}}$ be the sigma algebra on $\mathcal{S}$ and $(\mathcal{S}, \Sigma_{\mathcal{S}})$ represents the corresponding measurable space. The measure of households on $(\mathcal{S}, \Sigma_{\mathcal{S}})$ in period $t$ is denoted as $\Gamma_t$ and the stationary distribution is denoted as $\Gamma^\star$.

Given $\Gamma^\star$ and the sequence of energy price, a *competitive equilibrium* is a sequence of household decision rules for commuting energy consumption, residential energy consumption, non-energy consumption, labor supply, and asset holdings, $\{E_{Tt}(s),\ E_{Rt}(s),\ C_t(s),\ h_t(s),\ a_{t+1}(s)\}$; value functions $\{V_t(s)\}$; firm allocations $\{K_t, L_t, E_{Ft}\}$; government expenditures $\{G_t, T_t(s)\}$; non-energy factor prices $\{r_t, w_t\}$; and measures of households $\{\Gamma_t\}$ such that, for all $t$, the following conditions are satisfied:

(i) Household decision rules solve Bellman equations.

(ii) Firms maximize profits.

(iii) The government budget is balanced:

$$G_t + \int_{\mathcal{S}} T_t(s)\, d\Gamma_t = \tau^a r_t \int_{\mathcal{S}} a_t\, d\Gamma_t + \int_{\mathcal{S}} \mathcal{T}\left(z_t w_t h_t(s)\right) d\Gamma_t. \tag{11}$$

(iv) The capital market clears:

$$\int_{\mathcal{S}} a_t\, d\Gamma_t = K_t. \tag{12}$$

(v) The labor market clears:

$$\int_{\mathcal{S}} z_t h_t(s)\, d\Gamma_t = L_t. \tag{13}$$

Note that $L_t$ is the aggregate efficiency-weighted labor hours. Aggregate labor hours

can be expressed as

$$\int_{\mathcal{S}} h_t(s)\, d\Gamma_t = H_t. \tag{14}$$

(vi) The goods market clears:

$$Y_t = \int_{\mathcal{S}} C_t(s)\, d\Gamma_t + p_{Et} \int_{\mathcal{S}} \left(E_{Rt}(s) + E_{Tt}(s)\right) d\Gamma_t + p_{Et} E_{Ft}. \tag{15}$$

(vii) The evolution of capital follows equation (3).

### *4.8. Mechanisms*

In the model, an energy price shock impacts household consumption and labor supply decisions both directly and indirectly.

First, a change in energy price directly impacts household consumption by affecting their real income. This leads to adjustments in both their energy and non-energy consumption. Due to non-homothetic consumption preferences, these adjustments change the composition of household energy and non-energy consumption, which also vary across households in different income groups.

Second, a change in energy price changes household commuting costs, affecting the resources available for other consumption and investment. The resulting change in household consumption affects their marginal utility, consequently influencing their labor supply decisions. However, since household commuting costs depend on their earnings, ceteris paribus, any change in labor supply decisions will, in turn, affect their commuting costs. Thus, a trade-off between additional commuting costs and earnings influences both the direction and magnitude of labor supply adjustments.

Third, since energy serves as a factor input for non-energy production, a change in energy price directly impacts energy use in production due to costs. Consequently, firms adjust their composition of different factors, affecting their respective marginal productivities, leading to changes in wage and rental rate of capital. These adjustments, in turn, affect household consumption and labor supply decisions by influencing their income. In addition, an energy price shock indirectly impacts firms' decisions due to changes in demand

for non-energy goods in the economy. This change in demand occurs for two reasons. First, since all energy is imported and trade is balanced by exporting endogenously produced non-energy goods, a change in energy price impacts the demand for these goods. Second, as described earlier, an energy price shock influences household demand for non-energy consumption. Therefore, the aggregate demand for non-energy goods changes, affecting firms' demand for factors by impacting the scale of production.

## 5. PARAMETERIZATION

I now describe the calibration strategy of the model. The model period is set to one quarter. I specify pertinent functional forms and adopt a subset of model parameters directly from the literature. Among others, I obtain a subset of preference parameters by estimating the household demand system derived from the model. Table 2 presents these externally assigned and estimated parameter values. The remaining model parameters are determined jointly by matching an equal number of model moments—computed in the steady state equilibrium—with their corresponding empirical counterparts. Table 3 provides an overview of the internal calibration strategy and the calibrated parameter values.

### *5.1. Technology*

Following the literature, I set the output elasticity of capital $\alpha$ to 36%. Given my main focus on the short-run impacts of an energy price shock, in the baseline analysis, I abstract from technological progress and normalize $A_{Et}$ to 1. The base energy efficiency of production technology $\kappa$ is set to 20.0, ensuring that in the steady state, firms' expenditure on energy as a share of output matches its empirical counterpart (4.1%). The depreciation rate of capital $\delta$ is set to 1.53% per quarter, equivalent to a yearly depreciation rate of 6%.

### 5.2. *Idiosyncratic Productivity Shocks*

I calibrate the stochastic process for the idiosyncratic productivity shock following a two-step procedure. First, I assume productivity follows an AR(1) process in logs:

$$\log z_t = \rho_z \log z_{t-1} + \sigma_z \varepsilon_{zt}, \tag{16}$$

where $\rho_z \in (0,1)$ is the persistence of shocks, $\varepsilon_{zt} \in \mathbb{R}$ is a standard normal shock, and $\sigma_z \geq 0$ denotes the volatility of shocks. Following Floden and Lindé (2001), I assign the persistence $\rho_z$ to 0.975 and the standard deviation $\sigma_z$ to 0.165.

Second, based on Castañeda, Díaz-Giménez, and Ríos-Rull (2003), I incorporate the realization of an extreme productivity outcome denoted as $z_{\max}$, which can only be reached from the upper half of the normal productivity states with the same probability. I introduce two additional parameters, $\pi_{\text{up}}$ and $\pi_{\text{stay}}$, where $\pi_{\text{up}}$ represents the probabilities of transitioning from $z$ to $z_{\max}$ and $\pi_{\text{stay}}$ represents the probability of remaining at $z_{\max}$. I set these three parameters to match three specific data moments: (i) the wealth share of the top wealth decile (64.92%); (ii) the earnings share of the top earnings decile (35.58%); and (iii) the earnings share of the top 1% of the earnings distribution (11.59%).[13] This procedure yields $z_{\max} = 24.73$, $\pi_{\text{up}} = 2.21 \times 10^{-3}$, and $\pi_{\text{stay}} = 0.96$.

### 5.3. *Preferences*

I set the time discount factor $\beta$ to match the annual after-tax rate of return to assets of 4.1% in the steady state (McGrattan and Prescott, 2003; Gomme, Ravikumar, and Rupert, 2011). This procedure yields a value for $\beta$ of 0.977.

I specify the household's period utility function as

$$u(\boldsymbol{x}, h) = u_x(\boldsymbol{x}) - u_h(h), \tag{17}$$

13. All three data moments are computed using data from the biennial waves of the Panel Study of Income Dynamics (PSID) from 1999 to 2013 for household heads aged 25-64.

with

$$u_x(\boldsymbol{x}) = \begin{cases} \dfrac{\boldsymbol{x}^{1-\gamma}-1}{1-\gamma} & \text{if} \quad \gamma \neq 1; \\ \log \boldsymbol{x} & \text{if} \quad \gamma = 1, \end{cases} \tag{18}$$

and

$$u_h(h) = \varphi_1 \frac{h^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}} + \varphi_2 \cdot \mathbb{1}_{\{h>0\}}, \tag{19}$$

where $\gamma \geq 0$ governs the relative risk aversion, $\nu \geq 0$ represents the Frisch elasticity of labor supply, $\varphi_1 \geq 0$ determines the utility cost from intensive margin labor supply, and $\varphi_2 \geq 0$ is a fixed utility cost from working positive hours. The indicator function, $\mathbb{1}_{\{h>0\}}$, is equal to zero if $h = 0$ and equal to one when $h > 0$.

I set the coefficient of relative risk aversion $\gamma$ to 2, a commonly used value in the literature. The household level Frisch elasticity of labor supply $\nu$ is set to 0.5, which is consistent with the microeconomic evidence on the Frisch elasticity (see, e.g., Keane, 2011). The weight on the intensive margin labor supply component of utility $\varphi_1$ is set to 15.52, ensuring that in the steady state, the average hours worked are equal to one-third of the time endowment. I set the fixed utility cost from working $\varphi_2$ to 0.32, such that the model reproduces the aggregate employment rate of 80.20% in the steady state.

In the household's utility function, the consumption basket, $\boldsymbol{x}$, is an aggregate of residential energy ($E_R$) and non-energy ($C$) consumption, aggregated using a non-homothetic CES aggregator based on Comin, Lashkari, and Mestieri (2021). Thus, the household's consumption basket, $\boldsymbol{x}$, is implicitly defined as follows:

$$1 = \left[ \Omega_{E_R}^{\frac{1}{\sigma}} \left( \frac{E_R}{\boldsymbol{x}^{\epsilon_{E_R}}} \right)^{\frac{\sigma-1}{\sigma}} + \Omega_C^{\frac{1}{\sigma}} \left( \frac{C}{\boldsymbol{x}^{\epsilon_C}} \right)^{\frac{\sigma-1}{\sigma}} \right], \tag{20}$$

where $\sigma \geq 0$ measures the elasticity of substitution across goods, $\Omega_{E_R} \geq 0$ and $\Omega_C \geq 0$ are good-specific constant weight parameters. $\epsilon_{E_R}$ and $\epsilon_C$ are good-specific non-homotheticity parameters that determine the household's consumption elasticity of demand for respective goods. Equation (20) embeds the property of non-homothetic consumption preferences that can rationalize the systemic variation in different types of goods demanded at different

income levels.[14] The usual consumption aggregators typically assumed under homothetic CES preferences are a particular case of equation (20) with $\epsilon_C = \epsilon_{E_R} = 1$.

The household's optimal demand for residential energy and non-energy goods are:

$$E_R = \Omega_{E_R} \left( \frac{p_E}{Exp} \right)^{-\sigma} \boldsymbol{x}^{\epsilon_{E_R}(1-\sigma)}; \tag{21}$$

$$C = \Omega_C \left( \frac{p_C}{Exp} \right)^{-\sigma} \boldsymbol{x}^{\epsilon_C(1-\sigma)}. \tag{22}$$

where $Exp$ denotes the household's expenditure on the consumption basket. I estimate the above demand system using quarterly U.S. household consumption expenditure data from the CEX and disaggregated regional quarterly price series from the BLS and obtain the elasticity of substitution and the non-homotheticity parameters. The estimation approach closely follows the methodology used in the previous literature, particularly Comin, Lashkari, and Mestieri (2021). A concise description of the estimation exercise is provided in the main text, while further details are available in Appendix C. To obtain the estimating equation, I begin by expressing the ratio of household's expenditure shares on residential energy ($\omega_{E_R}$) and non-energy ($\omega_C$) goods:

$$\begin{aligned} \ln\left(\frac{\omega_{E_R}}{\omega_C}\right) = (1-\sigma)\ln\left(\frac{p_E}{p_C}\right) + (1-\sigma)(\epsilon_{ER}-1)\ln\left(\frac{Exp}{p_C}\right) \\ + (\epsilon_{E_R}-1)\ln\omega_C + \underbrace{\ln\left(\Omega_{E_R}\right)}_{\text{constant}\equiv\zeta}, \end{aligned} \tag{23}$$

where without loss of generality, I normalize $\epsilon_C = \Omega_C = 1$. The variables on the right- and left-hand side of equation (23) are observable in the data. I estimate an empirical counterpart of the above equation and report the estimation results in Table 1.[15]

I set the remaining preference parameter $\Omega_{E_R}$ to match average household expenditure share on residential energy in the steady state with its empirical counterpart of 7.20% from the CEX. This procedure yields a value for $\Omega_{E_R}$ of 0.10.

14. See Matsuyama (2019) and Comin, Lashkari, and Mestieri (2021) for details.
15. In Appendix C, I show the expenditure elasticities computed using the structurally estimated parameter values are consistent with their respective reduced-form estimates.

**TABLE 1**
DEMAND ESTIMATION

| Parameter | (1) | (2) | (3) |
|---|---|---|---|
| $\sigma$ | 0.251*** | 0.303*** | 0.248*** |
| | (0.015) | (0.014) | (0.021) |
| $\epsilon_{E_R}$ | 0.328*** | 0.301*** | 0.346*** |
| | (0.017) | (0.017) | (0.020) |
| Region FE | $\mathcal{X}$ | ✓ | ✓ |
| Year × Quarter FE | $\mathcal{X}$ | $\mathcal{X}$ | ✓ |

*Note*. All regressions include household controls: age (25-37, 38-50, 51-64), household size ($\leq$2, 3-4, 5+), and the number of earners (1, 2+). Standard errors clustered at the household level are shown in parentheses. The number of observations is 130,132 in all regressions. *** indicates significance at the 1% level.

### *5.4. Tax and Transfer System*

The tax and transfer system is parameterized to mimic key features of the U.S. tax and transfer system. I specify government consumption, $G$, as a fraction $g$ of aggregate output. $g$ is set to 20%, which corresponds to the average share of government purchases (consumption plus investment) to GDP in the U.S. for the past three decades. Following the literature, I set the capital income tax rate $\tau^a$ to 36% (see, e.g., Trabandt and Uhlig, 2011; Ferraro and Valaitis, 2023).

To capture the U.S. earnings tax progressivity, I use a parametric specification of the tax system according to which taxes on earnings are defined as follows:

$$\mathcal{T}(y) = y - \lambda y^{1-\tau^l}, \tag{24}$$

where $y$ denotes pre-tax earnings. $\tau \in [-1, 1]$ indexes the degree of tax progressivity such that $\tau^l \in [-1, 0)$ implies regressive tax system, $\tau^l = 0$ corresponds to flat tax system with a rate $1 - \lambda$, $\tau^l \in (0, 1)$ represents progressive tax system and, $\tau^l = 1$ means complete redistributive tax system.[16] Following Heathcote, Storesletten, and Violante (2020), I set

16. A tax schedule is commonly classified progressive (regressive) if the ratio of marginal to average tax rates is greater (smaller) than 1 for every level of income. According to my setup, I have

$$\frac{1 - \mathcal{T}'(y)}{1 - \frac{\mathcal{T}(y)}{y}} = 1 - \tau^l,$$

which implies that for $0 < \tau^l < 1$, marginal tax rates always exceed average tax rates. Consequently, with $\tau^l$

**TABLE 2**
EXTERNALLY SET AND ESTIMATED PARAMETERS

| Parameter | Description | Value | Source |
|---|---|---|---|
| *Technology parameters*: | | | |
| $\alpha$ | Output elasticity of capital | 0.36 | Literature |
| $\delta$ | Depreciation rate of capital | 0.015 | Literature |
| *Idiosyncratic labor productivity parameters*: | | | |
| $\rho_z$ | Persistence of productivity shocks | 0.975 | Floden and Lindé (2001) |
| $\sigma_z$ | Standard deviation of productivity innovations | 0.165 | Floden and Lindé (2001) |
| *Preference parameters*: | | | |
| $\gamma$ | Risk aversion coefficient | 2.0 | Literature |
| $\sigma$ | ES between energy and non-energy consumption goods | 0.248 | Demand estimation (column 4 of Table 1) |
| $\epsilon_{E_R}$ | Non-homotheticity parameter of energy consumption | 0.346 | Demand estimation (column 4 of Table 1) |
| $\epsilon_C$ | Non-homotheticity parameter of non-energy consumption | 1.0 | Normalization |
| $\Omega_C$ | Weight of non-energy goods in the consumption basket | 1.0 | Normalization |
| $\nu$ | Frisch elasticity of labor supply | 0.50 | Literature |
| *Tax & transfer parameters*: | | | |
| $\tau^a$ | Capital income tax rate | 0.36 | Trabandt and Uhlig (2011) |
| $\tau^l$ | Curvature of the earnings tax function | 0.09 | Heathcote, Storesletten, and Violante (2020) |

*Note.* Abbreviation: ES, elasticity of substitution.

$\tau^l$ to 0.09, an estimate obtained by excluding transfers from disposable income. Given $\tau^l$ and government expenditures, $\lambda$ balances the government budget. This procedure yields a value for $\lambda$ of 0.84. $\lambda$ allows the tax function to shift without affecting the degree of tax progressivity and determines the average level of earnings tax in the economy.

The tax function $\mathcal{T}(\cdot)$ has a long tradition in public economics, first proposed by Feldstein (1969) and more recently used by Bénabou (2000, 2002), and Heathcote, Storesletten, and Violante (2017). It fits the U.S. data well, except for the bottom decile of the U.S. income distribution (Heathcote, Storesletten, and Violante, 2020). The observed discrepancy can be attributed to two reasons. Firstly, the tax function implies that marginal taxes are

in that interval, the tax system is progressive, and conversely, when $\tau^l < 0$, the tax system is regressive. The case $\tau^l = 0$ implies that marginal and average tax rates are equal, corresponding to the flat tax system.

monotone in income. However, marginal tax rates can be high at the bottom of the income distribution due to the phasing out of means-tested programs. Secondly, this tax schedule lacks a floor for disposable income, meaning households with zero pre-tax income also have zero after-tax income. Nevertheless, in the U.S., programs such as the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF), and Unemployment Insurance (UI) guarantee a floor.

Similar to the U.S. economy, the means-tested transfer program in the model also ensures a minimum level of support for non-employed households. I set the maximum possible lump-sum transfer to a non-employed household $\bar{e}$ to 0.33, ensuring that in the steady state, the average transfers-to-income ratio of the lowest wealth quintile is 16.3%.

### *5.5. Energy Usage in Commuting*

I specify energy use for commuting as $E_T(zwh) = \iota_0 \left[\log(1 + zwh)\right]^{\iota_1}$, where $\iota_0 > 0$ is the scaling parameter and $\iota_1 > 0$ is the sensitivity of energy consumption for commuting to household earnings. $E_T(\cdot)$ increases with household earnings, implying that households with higher earnings typically require more energy for commuting to work than those with lower earnings, often because the former tend to live farther from their workplaces. This concept aligns with the evidence on commuting time found in the American Time Use Survey (ATUS) (see Kimbrough, 2019).[17]

I set $\iota_0$ to 0.03, ensuring that, in the steady state, employed households' average expenditure share on commuting energy matches its empirical counterpart (2.0%). The sensitivity parameter $\iota_1$ is set to 0.74 so that the ratio of bottom-to-top income quintile employed households' expenditure share on commuting energy in the steady state matches its corresponding data moment (1.37).

17. This direct relationship between income and commuting costs also aligns with the intuition of the classic model of urban spatial structure outlined in Mills (1967) and Muth (1969). Alternatively, in my model, the consumer unit is defined as a household. Hence, an increase in hours worked in the model, resulting in higher earnings at a given level of labor productivity, can be interpreted as an increase in the number of earners in the household and its corresponding expenditure on commuting energy. This interpretation is supported by evidence from the CEX, as shown in Figure F.4—the expenditure on commuting energy increases with the number of earners in the household.

**TABLE 3**
INTERNALLY CALIBRATED PARAMETERS

| Parameter | Description | Value | Target |
|---|---|---|---|
| *Technology parameters*: | | | |
| $\kappa$ | Base energy efficiency in production | 20.0 | Firms' expenditure on energy as a share of GDP (4.1%) |
| *Idiosyncratic labor productivity parameters*: | | | |
| $z_{\max}$ | Extreme productivity state | 24.725 | Wealth share of top wealth decile (64.92%) |
| $\pi_{\text{up}}$ | Probability of transitioning from $z$ to $z_{\max}$ | 0.002 | Earnings share of top earnings decile (35.58%) |
| $\pi_{\text{stay}}$ | Probability of remaining at $z_{\max}$ | 0.962 | Earnings share of top 1% of the earnings distribution (11.59%) |
| *Preference parameters*: | | | |
| $\beta$ | Discount factor | 0.977 | After-tax rate of return (4.1%) |
| $\Omega_{E_R}$ | Weight of $E_R$ in the consumption basket | 0.103 | Households' average expenditure share on $E_R$ (7.20%) |
| $\varphi_1$ | Determinant of the utility cost of intensive margin labor supply | 15.519 | Average hours worked as a share of total time endowment (33.33%) |
| $\varphi_2$ | Fixed utility cost of working | 0.316 | Employment rate (80.20%) |
| *Tax & transfer parameters*: | | | |
| $\lambda$ | Government budget balancer | 0.838 | Government purchases as a share of GDP (20.0%) |
| $\bar{e}$ | Maximum possible lump-sum transfer | 0.327 | Average transfers-to-income ratio of the lowest wealth quintile (16.3%) |
| *Other parameters*: | | | |
| $\iota_0$ | Scaling factor for $E_T$ | 0.032 | Working households' average expenditure share on $E_T$ (2.00%) |
| $\iota_1$ | Sensitivity of $E_T$ to household income | 0.737 | Ratio of bottom-to-top income quintile worker expenditure share on $E_T$ (1.37) |
| $\underline{a}$ | Borrowing limit | $-0.071$ | Share of households with negative wealth (15.0%) |

*Note*. Abbreviation: GDP, gross domestic product.

### *5.6. Borrowing Limit*

The exogenous borrowing limit $\underline{a}$ is set to ensure that in the steady state, the model matches the share of households with negative assets in the data (15.0%). This procedure yields a value of $\underline{a}$ equal to $-0.07$, which is equivalent to $-4\%$ of per-capita pre-tax income.

## 6. MODEL FIT

In this section, I assess how well my model replicates the U.S. economy in relevant dimensions. All model statistics presented here are computed in the steady state. Table 4

**TABLE 4**
TARGETED MOMENTS: BASELINE

| Moment | Data | Model |
|---|---|---|
| Firms' expenditure on energy as a share of GDP | 4.10% | 4.10% |
| Wealth share of top wealth decile | 64.92% | 69.92% |
| Earnings share of top earnings decile | 35.58% | 46.44% |
| Earnings share of top 1% of the earnings distribution | 11.59% | 17.97% |
| After-tax rate of return | 4.10% | 4.15% |
| Households' average expenditure share on $E_R$ | 7.20% | 7.25% |
| Average hours worked as a share of total time endowment | 33.33% | 33.50% |
| Employment rate | 80.20% | 80.44% |
| Government purchases as a share of GDP | 20.0% | 20.0% |
| Average transfers-to-income ratio of the lowest wealth quintile | 16.30% | 14.31% |
| Working households' average expenditure share on $E_T$ | 2.00% | 2.01% |
| Ratio of bottom-to-top income quintile worker expenditure share on $E_T$ | 1.37 | 1.36 |
| Share of households with negative wealth | 15.0% | 14.87% |

*Note*. The table presents targeted moments in the baseline model calibration along with their empirical counterparts. All model moments are computed in the steady state.

compares the targeted data moments and their corresponding values in the model. Following that, I present the model's performance in replicating the cross-sectional distributions of employment, wealth, earnings, and expenditure share on energy—dimensions not comprehensively targeted in the calibration.

Figure 5 compares the employment rates by income quintiles in the model and the data, while Figure 6 compares the household earnings and wealth distributions. In the U.S., earnings and wealth distributions are highly concentrated and skewed to the right (see, e.g., Castañeda, Díaz-Giménez, and Ríos-Rull, 2003; Diaz-Gimenez, Glover, and Ríos-Rull, 2011; Kuhn and Ríos-Rull, 2016). The figure shows that the model successfully captures this right-skewed nature of the distributions, aligning closely with the share of earnings and wealth for each quintile of households calculated from the data.

The two key features of my model are the non-homothetic consumption preferences and the explicit inclusion of commuting costs. These features are incorporated aiming to capture the cross-sectional distribution of expenditure shares on residential and commuting energy. Figure 7 compares the household expenditure shares on energy consumption

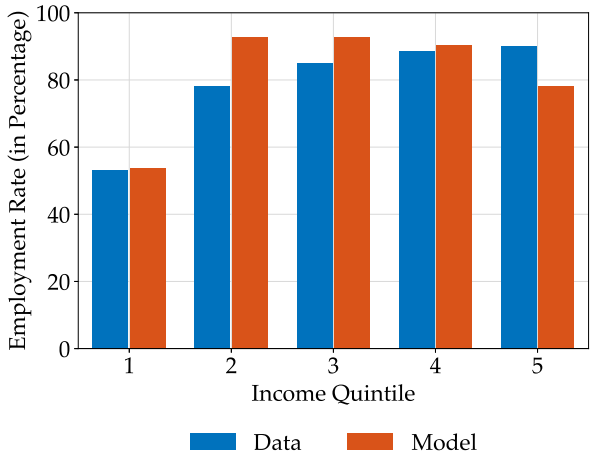
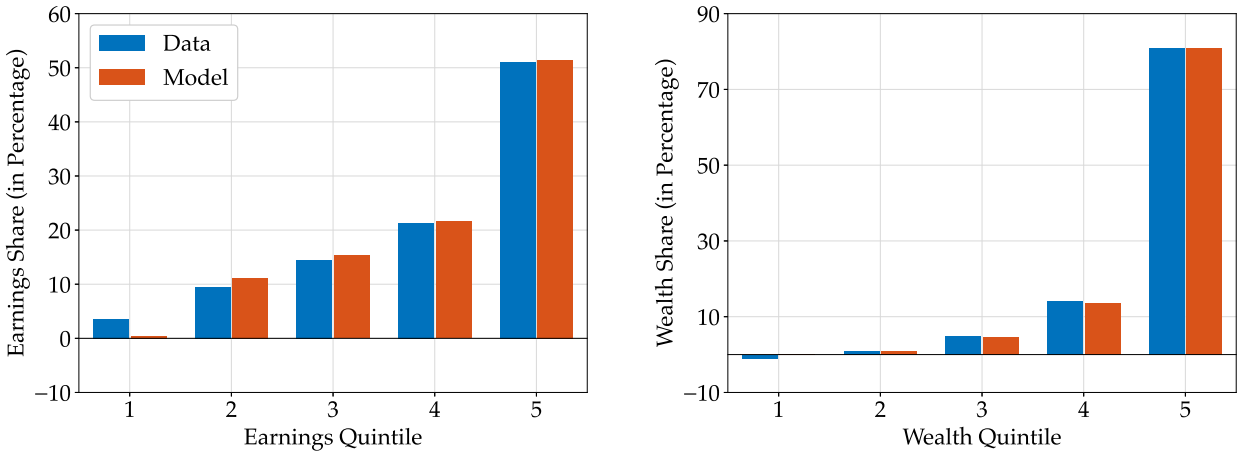



**FIGURE 5**
EMPLOYMENT RATE BY INCOME QUINTILES – MODEL VS. DATA

*Note.* The figure shows the distribution of employment rates by income quintiles in the model and the data. The empirical moments are calculated using the biennial waves of the PSID from 1999 to 2013 for household heads aged 25-64.



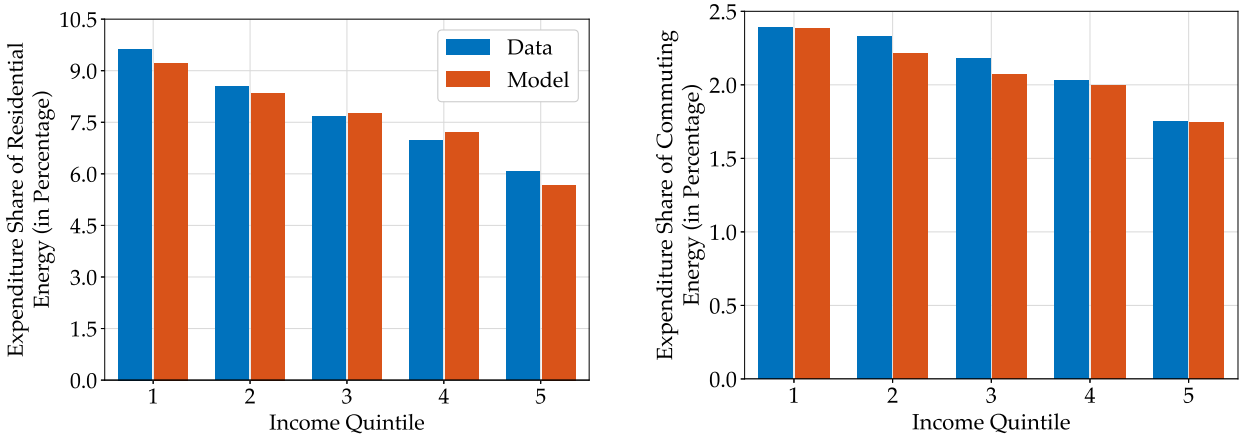

**(A)** EARNINGS DISTRIBUTION

**(B)** WEALTH DISTRIBUTION

**FIGURE 6**
EARNINGS AND WEALTH DISTRIBUTIONS – MODEL VS. DATA

*Note.* The figure shows the distributions of earnings (Panel A) and wealth (Panel B) in the model and the data. The empirical moments are calculated using the biennial waves of the PSID from 1999 to 2013 for household heads aged 25-64. Wealth is defined as total assets minus total liabilities at the household level.

for residential purposes (Panel A) and commuting (Panel B) between the model and the data. The figure shows that the model effectively reproduces observed expenditure shares across income quintiles for both types of energy consumption.




**(A)** DISTRIBUTION OF EXPENDITURE SHARE ON RESIDENTIAL ENERGY

**(B)** DISTRIBUTION OF EXPENDITURE SHARE ON COMMUTING ENERGY

**FIGURE 7**
DISTRIBUTIONS OF HOUSEHOLD EXPENDITURE SHARE ON RESIDENTIAL AND COMMUTING ENERGY – MODEL VS. DATA

*Note.* The figure shows the distributions of household expenditure shares for residential (Panel A) and commuting (Panel B) energy consumption in the model and the data. The empirical moments are calculated using the quarterly waves of the CEX from 1999 to 2013 for households with reference persons aged 25-64 who participated in at least four interviews and are complete income reporters.

Overall, the calibrated version of the model reproduces many salient features of the U.S. data and provides a cross-sectionally rich, empirically informed framework. I now use this calibrated model as a laboratory for my quantitative analysis.

## 7. QUANTITATIVE ANALYSIS

In this section, I conduct a set of quantitative experiments to examine the effects of an energy price shock. Specifically, I derive fully nonlinear perfect-foresight impulse responses to a shock starting from a steady state without aggregate uncertainty.[18] First, using the baseline calibrated model, I explore the effects of an inflationary energy price shock on households across different income groups. Next, I explore the variations in shock responses due to changes in its direction, variance, and persistence. Finally, I explore the impact of WFH opportunities and targeted transfer programs on the baseline responses.

18. This type of shock is known as "MIT Shock" (see Boppart, Krusell, and Mitman, 2018). By certainty equivalence, the impulse responses derived from a model with MIT shock are the same as those from the model with aggregate risk (see Auclert, Bardóczy, Rognlie, and Straub, 2021).

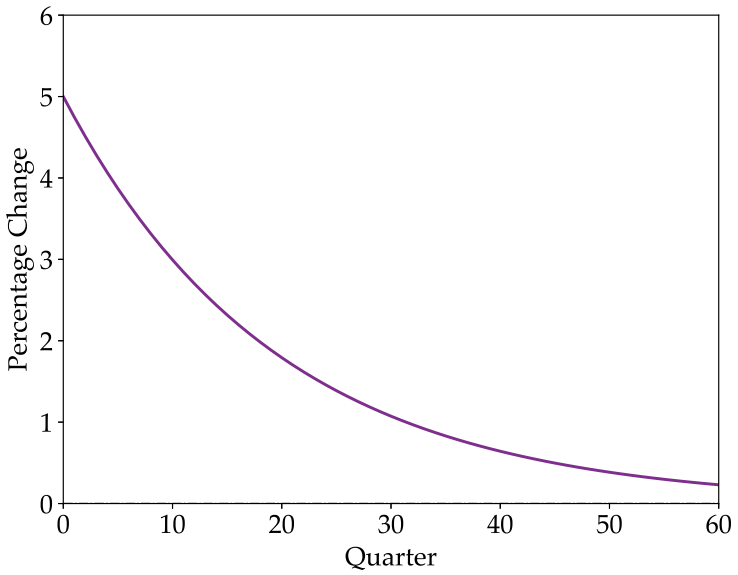



**FIGURE 8**
ENERGY PRICE PATH

### *7.1. Energy Price Shock*

I assume that a shock to the energy price is AR(1).[19] Therefore, $p_{Et}$ is determined by

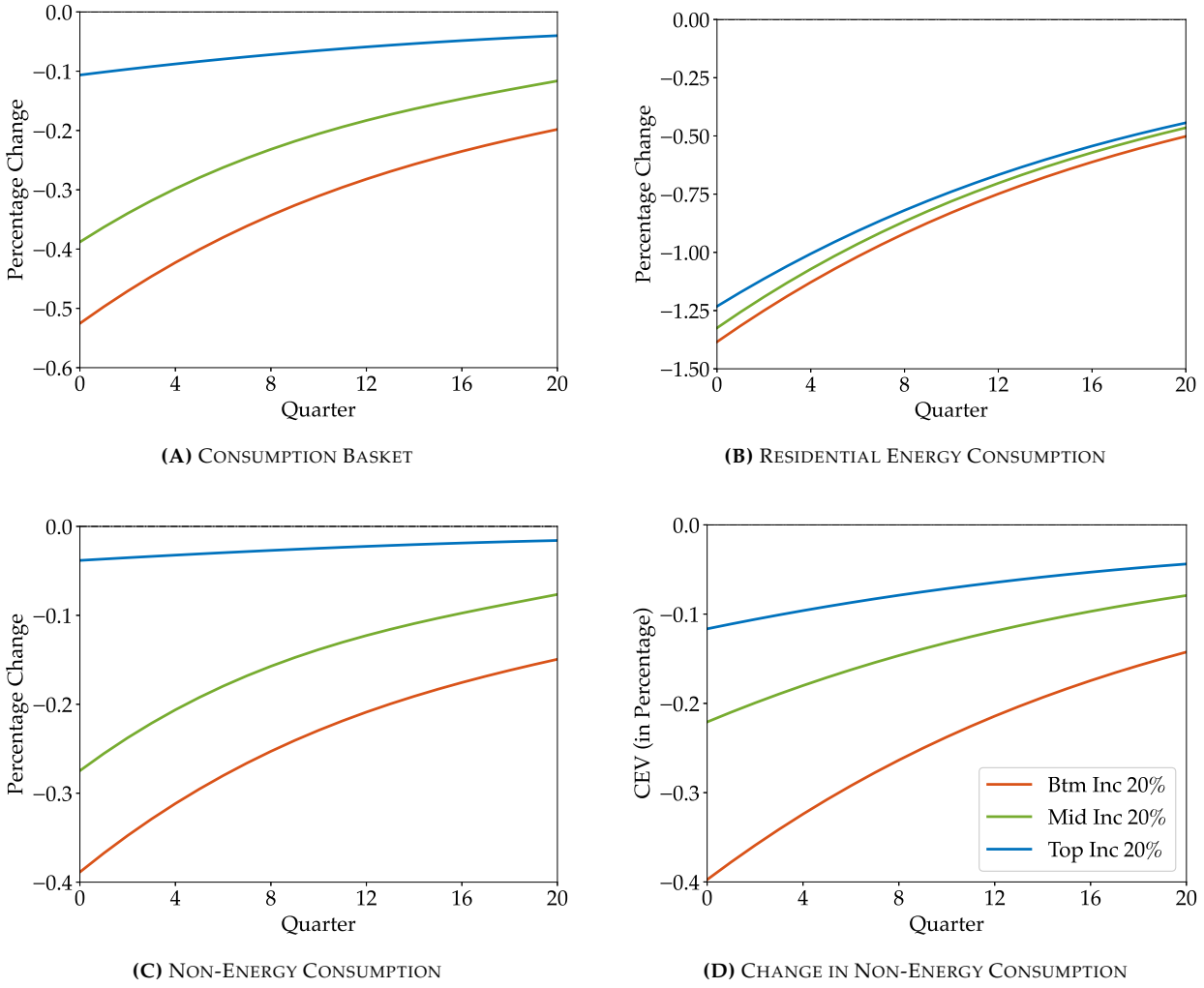
$$\log p_{Et} = \rho_E \log p_{E,t-1} + \sigma_E \varepsilon_{Et}, \tag{25}$$

where $\rho_{Et} \in (0,1)$ is the persistence, $\sigma_E > 0$ is the volatility, and $\varepsilon_{Et} \in \mathbb{R}$ is the innovation of $p_{Et}$. The economy is initially in a steady state and unexpectedly experiences a shock to energy price that causes $p_{Et}$ to change by one standard deviation. Following the shock, the path of $p_{Et}$ is determined as shown in Figure 8.

### *7.2. Effects of an Inflationary Energy Price Shock*

For the baseline analysis, I choose an inflationary energy price shock with a persistence of $\rho_{p_E} = 0.95$, equivalent to a shock with a half-life (i.e., the time it takes for the shock's effect to halve in magnitude) of approximately four years, and volatility of $\sigma_{p_E} = 0.05$.

19. It is important to mention that using an augmented Dickey-Fuller test, I cannot reject the null hypotheses of a unit root in the energy price process at a 1% level of significance. However, it is challenging to derive impulse responses to a non-stationary shock. Therefore, the literature often treats energy price shocks as stationary (e.g., Kim and Loungani, 1992; Kuhn, Kehrig, and Ziebarth, 2021; Auclert, Monnery, Rognlie, and Straub, 2023). Addressing this limitation could be a valuable direction for future research.




**(A)** CONSUMPTION BASKET

**(B)** RESIDENTIAL ENERGY CONSUMPTION

**(C)** NON-ENERGY CONSUMPTION

**(D)** CHANGE IN NON-ENERGY CONSUMPTION

**FIGURE 9**
DISTRIBUTIONAL EFFECTS OF AN INFLATIONARY ENERGY PRICE SHOCK ON HOUSEHOLD CONSUMPTION AND WELFARE ($\rho_{p_E} = 0.95; \sigma_{p_E} = 0.05$)

The increase in energy price raises households' consumption expenditure, reducing their real income and compelling a rise in labor supply. The labor supply responses vary across households in both extensive and intensive margins. Low-income households, with their higher marginal utility, are more inclined to increase their labor supply to compensate for their consumption drop. This is because low-income households, lacking savings to insure against the price shock, rely on increasing their labor supply to smooth consumption. However, a higher labor supply generates additional welfare losses, as higher commuting costs limit other consumption, and reduced leisure diminishes utility.

As shown in Figure 9 Panel A, the size of the consumption basket decreases for house-

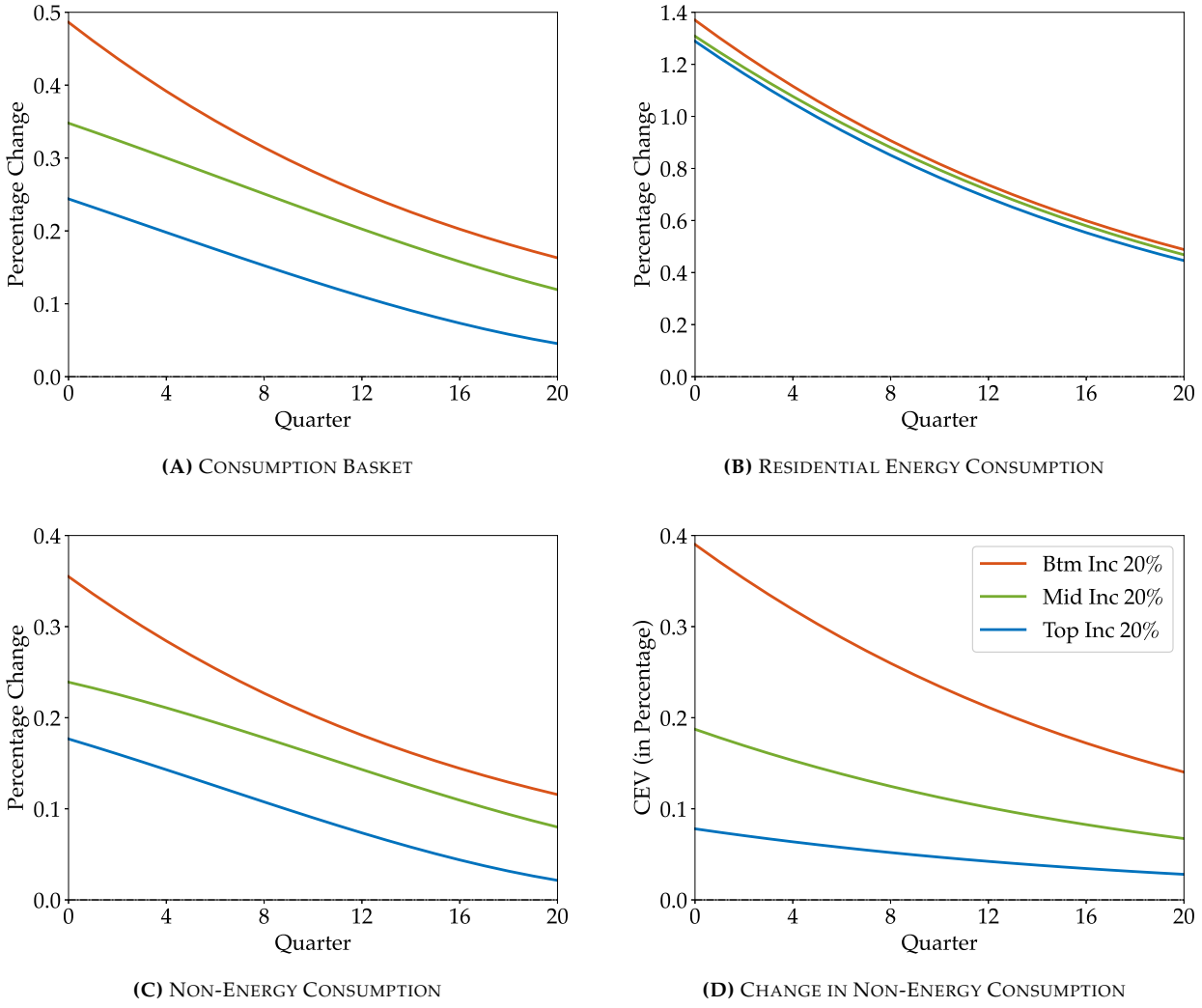
holds in the lowest income quintile five times more than the top quintile. This decline in consumption basket occurs due to the decrease in both energy and non-energy consumption. Panel B shows that residential energy consumption decreases approximately the same across households in different income groups. However, Panel C shows that the varying decline in non-energy consumption is responsible for the disproportionate decline in the size of the consumption basket. Panel D shows that households in the lowest income quintile experience welfare losses four times more than those in the top income quintile.

### *7.3. Comparison with Alternative Models*

In addition to the baseline scenario of an inflationary energy price shock, I examine the effects of a deflationary energy price shock to directly compare the outcomes of different shock types in my model. To do that, I choose the same parameter values for the persistence and volatility of the shock as the baseline scenario. Figure 10 shows the effects of the shock on the consumption and welfare of households across various income groups. The figure shows that the increase in consumption exceeds the declines observed in the inflationary shock scenario. Nonetheless, the welfare gains are marginally lower than the welfare losses in the baseline scenario, which aligns with intuitions given the concave utility function.

Next, I explore the effects of an inflationary energy price shock with the same persistence as the baseline case, but on impact, this shock increases the relative energy price by half of the increase in the baseline case. The results of this exercise are presented in Figure 11. The figure shows that because of the small shock, the consumption and welfare impacts are approximately half of the baseline case.

I then explore the effects of an inflationary energy price shock with a lower persistence (i.e., $\rho_{p_E} = 0.90$) than the baseline case. With this reduced persistence, the half-life of the shock is two and a half years. Figure 12 shows that because of lower shock persistence, households across different income groups recover consumption at a higher rate than the baseline case.




**(A)** CONSUMPTION BASKET

**(B)** RESIDENTIAL ENERGY CONSUMPTION

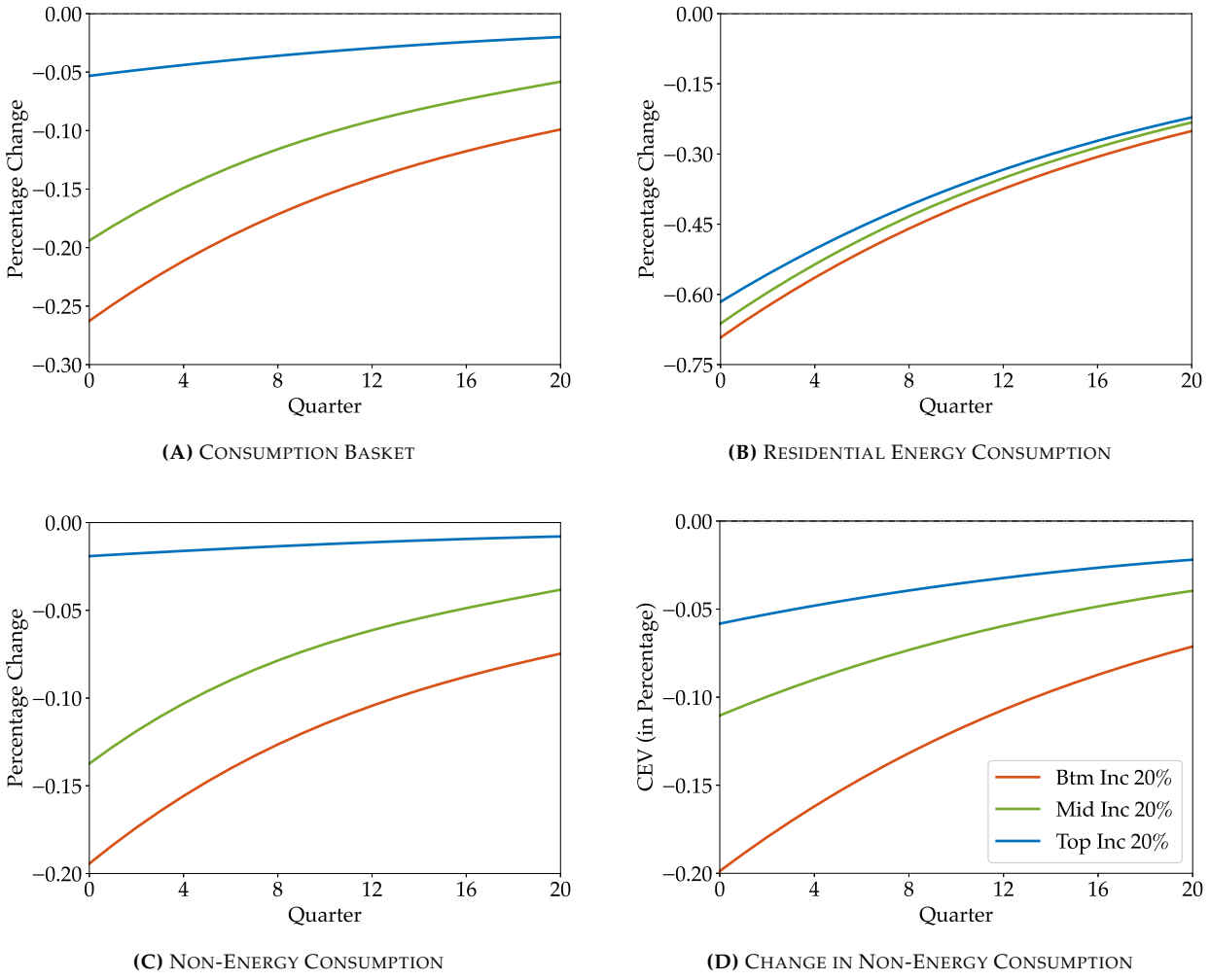
**(C)** NON-ENERGY CONSUMPTION

**(D)** CHANGE IN NON-ENERGY CONSUMPTION

**FIGURE 10**
DISTRIBUTIONAL EFFECTS OF AN DEFLATIONARY ENERGY PRICE SHOCK ON HOUSEHOLD CONSUMPTION AND WELFARE ($\rho_{p_E} = 0.95; \sigma_{p_E} = 0.05$)

### *7.4. Policy Analysis*

**Work from Home Opportunity.** Given the growing trend of WFH arrangements, especially since the COVID-19 pandemic, it is crucial to understand its impact on the effects of energy price shocks. WFH offers the advantage of significantly cutting commuting costs, allowing households to reallocate these resources to other consumption or investment. However, WFH opportunity is notably higher in high-skilled intensive jobs, such as education, financial, and information services, thus predominantly favoring high-skilled workers (see, e.g., Bick, Blandin, and Mertens, 2023; Barrero, Bloom, and Davis, 2023). This unequal access to




**(A)** CONSUMPTION BASKET

**(B)** RESIDENTIAL ENERGY CONSUMPTION

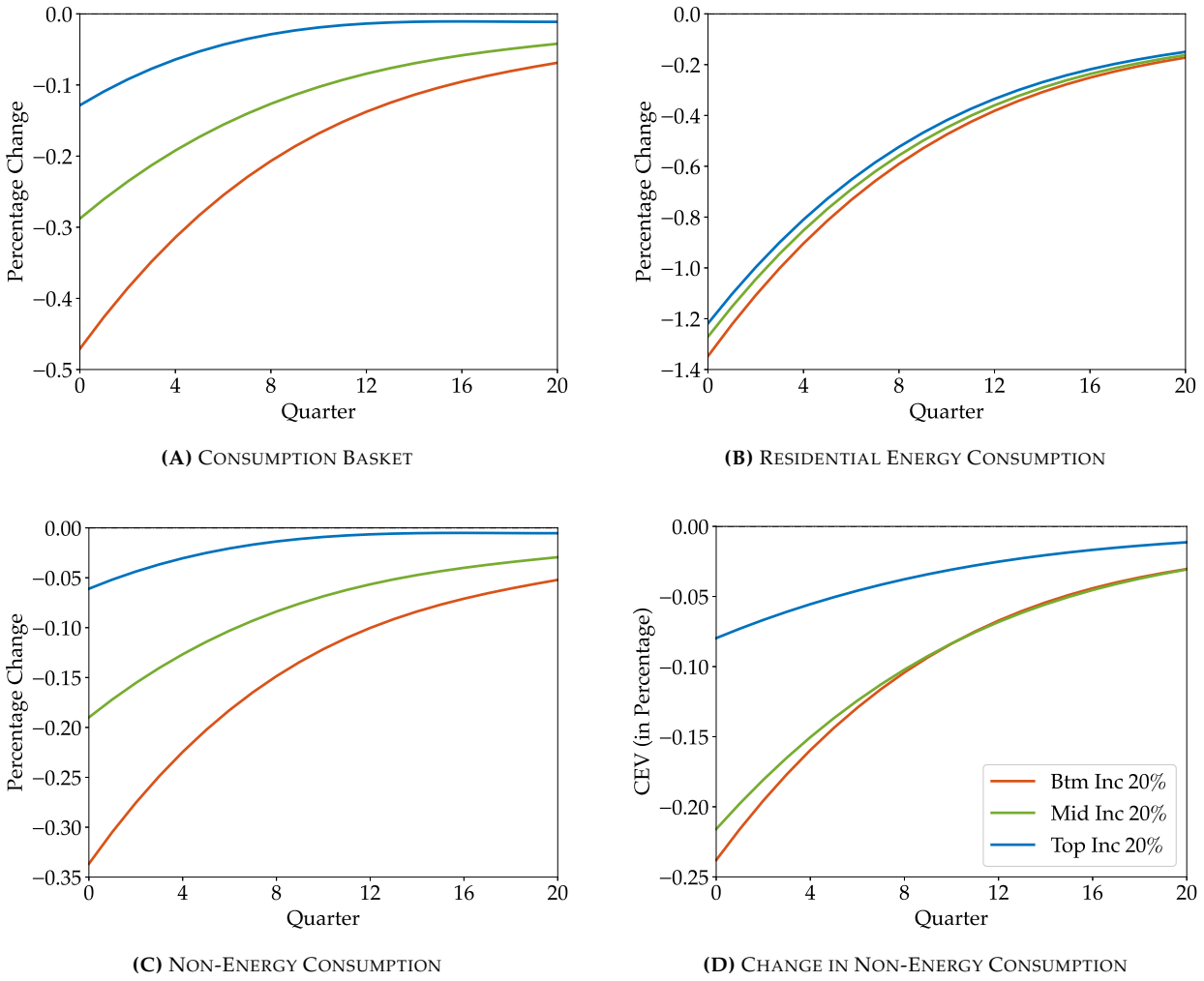
**(C)** NON-ENERGY CONSUMPTION

**(D)** CHANGE IN NON-ENERGY CONSUMPTION

**FIGURE 11**
DISTRIBUTIONAL EFFECTS OF AN INFLATIONARY ENERGY PRICE SHOCK ON HOUSEHOLD CONSUMPTION AND WELFARE ($\rho_{p_E} = 0.95; \sigma_{p_E} = 0.025$)

WFH opportunities exacerbates economic inequality, thereby influencing the distributional effects of energy price shocks.

To explore the implications of WFH, in my model, I exogenously allow the top quintile of the earnings distribution to WFH by reducing their commuting energy consumption to half of the usual level. This reduction in commuting costs leaves more resources for residential energy and non-energy consumption. In addition, the fall in the wage rate, coupled with the wealth effect, leads to a reduction in labor supply among the top income quintile. These factors collectively contribute to a welfare gain for the top quintile. In contrast, the bottom quintile still experiences similar welfare loss, thus exacerbating the




**(A)** CONSUMPTION BASKET

**(B)** RESIDENTIAL ENERGY CONSUMPTION

**(C)** NON-ENERGY CONSUMPTION

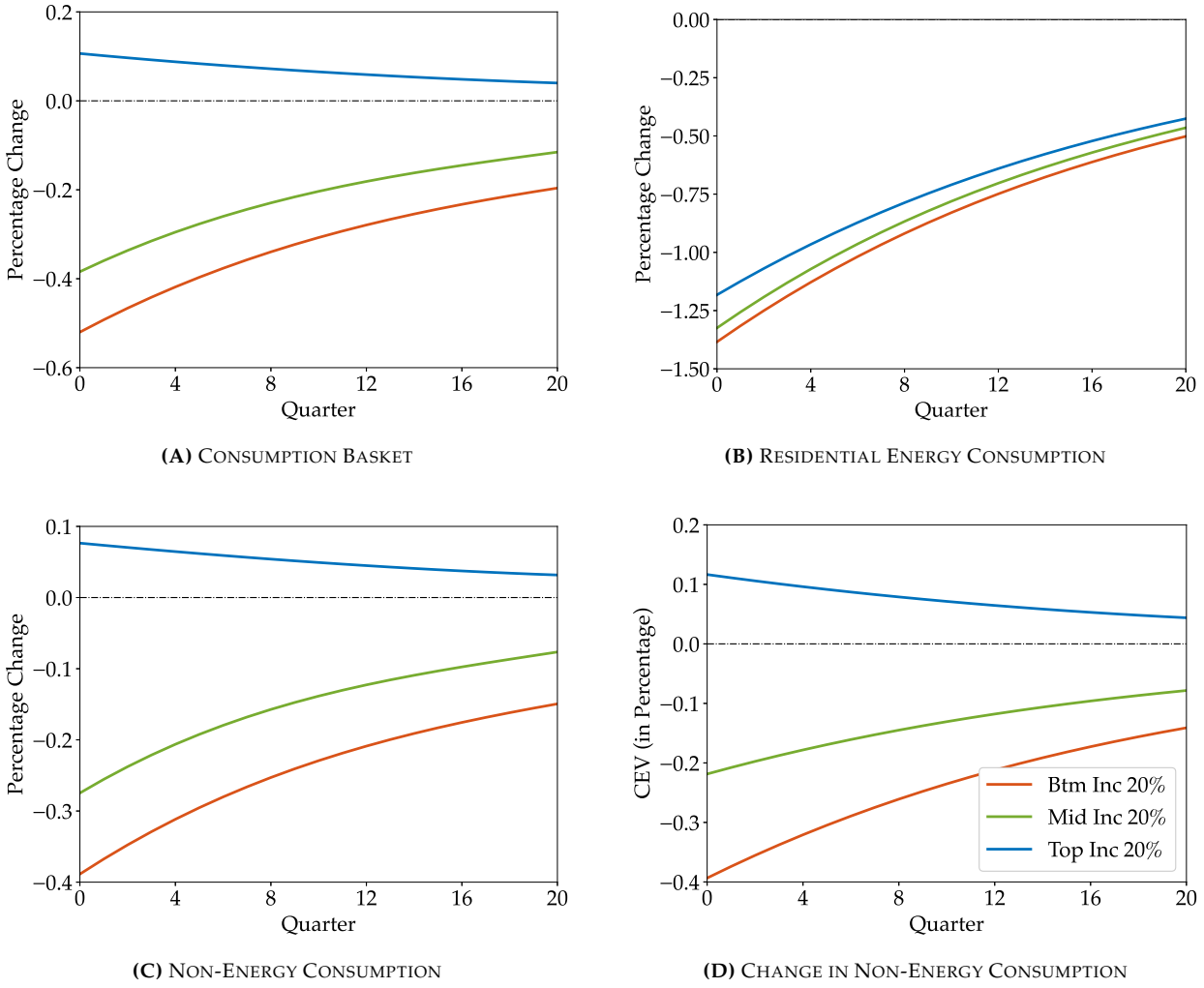
**(D)** CHANGE IN NON-ENERGY CONSUMPTION

**FIGURE 12**
DISTRIBUTIONAL EFFECTS OF AN INFLATIONARY ENERGY PRICE SHOCK ON HOUSEHOLD CONSUMPTION AND WELFARE ($\rho_{p_E} = 0.90; \sigma_{p_E} = 0.05$)

overall welfare disparity (Figure 12 Panel D).

**Targeted Transfer Program.** In the U.S., a federally funded program provides financial assistance to low-income households for their energy expenditures. The program is known as the Low Income Home Energy Assistance Program (LIHEAP). It specifically provides financial assistance for home energy expenses like heating and cooling. In Texas, the Department of Housing and Community Affairs has adapted LIHEAP to cover both gas and electric bills, renaming it the Comprehensive Energy Assistance Program (CEAP).[20] Moti-

20. To be eligible for CEAP, one must be at or below 150% of Federal Poverty Guidelines. A person who participates or has family members who receive SNAP, TANF, Supplemental Security Income (SSI), or certain




**(A)** CONSUMPTION BASKET

**(B)** RESIDENTIAL ENERGY CONSUMPTION

**(C)** NON-ENERGY CONSUMPTION

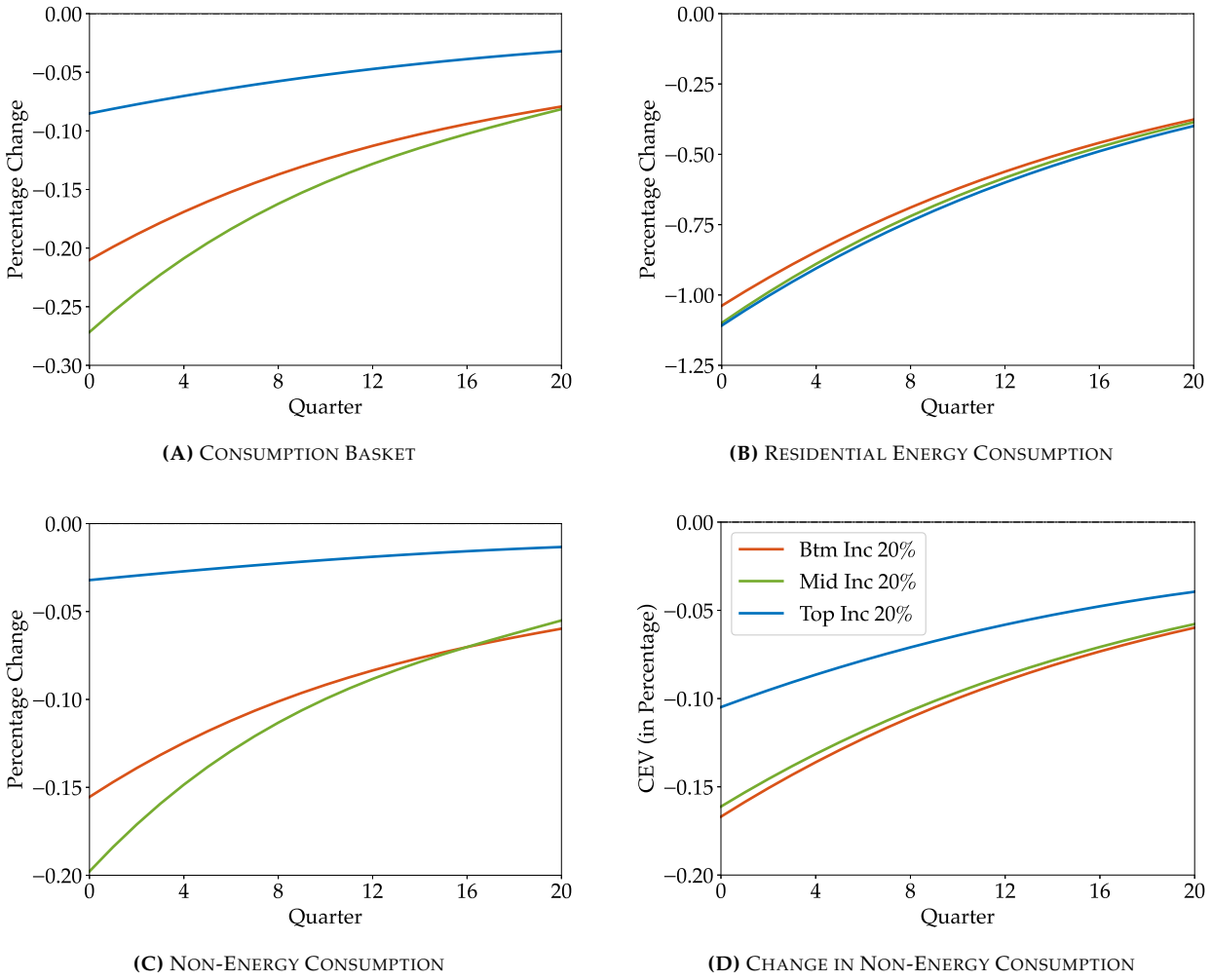
**(D)** CHANGE IN NON-ENERGY CONSUMPTION

**FIGURE 13**
IMPACT OF WORK-FROM-HOME OPPORTUNITY ON DISTRIBUTIONAL OUTCOMES FOLLOWING AN INFLATIONARY ENERGY PRICE SHOCK ($\rho_{p_E} = 0.95; \sigma_{p_E} = 0.05$)

vated by the energy assistance program, I now explore how a targeted transfer program influences inflationary energy price shock impacts in my model.

To implement the targeted transfer program, following an inflationary energy price shock, I provide a lump-sum transfer to households in the lowest income quintile in my model. The results of this exercise are presented in Figure 14. As shown in Panel A, this transfer significantly reduces the consumption loss of the targeted group. In addition, by providing insurance to low-income households, these programs reduce uncertainty in the incomplete market setting, thereby reducing the baseline welfare across the income distri-

Means Tested Veterans Program payments automatically meets the eligibility requirement.




**(A)** CONSUMPTION BASKET

**(B)** RESIDENTIAL ENERGY CONSUMPTION

**(C)** NON-ENERGY CONSUMPTION

**(D)** CHANGE IN NON-ENERGY CONSUMPTION

**FIGURE 14**
IMPACT OF A TARGETED TRANSFER PROGRAM ON DISTRIBUTIONAL OUTCOMES FOLLOWING AN INFLATIONARY ENERGY PRICE SHOCK ($\rho_{p_E} = 0.95; \sigma_{p_E} = 0.05$)

bution (Figure 14 Panel D).

## 8. CONCLUDING REMARKS

This paper studies the distributional effects of an energy price shock in a quantitative framework incorporating energy use in residential utilities, commuting, and production. It develops a heterogeneous-agent incomplete market model with several novel features, including non-homothetic consumption preferences, commuting costs, and a production technology that integrates energy and non-energy factor inputs in fixed proportions to

produce non-energy goods. A calibrated version of the model reproduces many salient features of the data, including the cross-sectional distribution of residential and commuting energy expenditure shares. A one-standard-deviation inflationary energy price shock in the model results in disproportionate welfare losses across income groups, with the lowest income quintile facing losses four times greater than the highest on impact, primarily due to their disproportionate non-energy consumption adjustments.

The paper also explores how WFH opportunities and targeted transfers influence the impact of energy price shock. It finds that WFH opportunities mainly benefit households that have such opportunities without notably affecting others. Consequently, the disproportionate WFH opportunities for high-skilled households exacerbate consumption and welfare inequality. On the other hand, targeted transfers to low-income households reduce welfare losses from an inflationary energy price shock across the income distribution by lowering uninsurable income risk.

The analysis in this paper can be extended in several dimensions in future research. First, while it is common in the literature to model energy as an imported good, incorporating a domestic energy production sector alongside energy imports can make the model even more realistic to the U.S. economy. Second, considering multiple non-energy sectors based on their energy intensity could be a meaningful extension. This is because energy price shocks may disproportionately affect sectors that heavily rely on energy, impacting all associated entities with these sectors. On the other hand, sectors with a lower dependency on energy might experience more muted effects. Finally, by distinguishing between dirty and clean energy consumption, one can explore how energy price shocks impact the clean energy transition of households across different income and wealth groups.

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## APPENDIX A: MATHEMATICAL DERIVATIONS

### *A.1. Household Problem*

The Lagrangian for a household is given by

$$\begin{aligned}\mathcal{L}_{it} =& \mathbb{E}_t\Bigg[\sum_{t=0}^{\infty}\beta^t\Bigg\{\left(\frac{\boldsymbol{x}_{it}^{1-\gamma}-1}{1-\gamma}-\varphi_1\frac{h_{it}^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}-\varphi_2\cdot\mathbb{1}_{\{h_{it}>0\}}\right)\\ &-\mu_{1it}\left(\sum\nolimits_j\Omega_j^{\frac{1}{\sigma}}\left(\frac{c_{ijt}}{\boldsymbol{x}_{it}^{\epsilon_j}}\right)^{\frac{\sigma-1}{\sigma}}-1\right)\\ &-\mu_{it}\Bigg(\sum\nolimits_j p_{jt}c_{ijt}+p_{Et}\,\iota_0\left[\log(1+z_{it}w_th_{it})\right]^{\iota_1}\cdot\mathbb{1}_{\{h_{it}>0\}}+a_{i,t+1}\\ &-(1+(1-\tau^a)\,r_t)\,a_{it}-\lambda_t\left(z_{it}w_th_{it}\right)^{1-\tau^l}-T\left(a_{it}\right)\cdot\mathbb{1}_{\{h_{it}=0\}}\Bigg)\Bigg\}\Bigg],\end{aligned} \tag{A.1}$$

where $\mu_{1it}$ and $\mu_{it}$ denote the Lagrange multipliers. $j$ denotes items in the household's consumption basket, $j=\{C,ER\}$.

The household first order conditions are:

$$[\boldsymbol{x}_{it}]:\ \boldsymbol{x}_{it}^{-\gamma}=\mu_{1it}\cdot\frac{1-\sigma}{\sigma}\cdot\frac{1}{\boldsymbol{x}_{it}}\left(\sum\nolimits_j\Omega_j^{\frac{1}{\sigma}}\left(\frac{c_{ijt}}{\boldsymbol{x}_{it}^{\epsilon_j}}\right)^{\frac{\sigma-1}{\sigma}}\epsilon_j\right); \tag{A.2}$$

$$[\boldsymbol{c}_{ijt}]:\ \mu_{1it}\cdot\frac{1-\sigma}{\sigma}\cdot\frac{1}{c_{ijt}}\cdot\Omega_j^{\frac{1}{\sigma}}\left(\frac{c_{ijt}}{\boldsymbol{x}_{it}^{\epsilon_j}}\right)^{\frac{\sigma-1}{\sigma}}=\mu_{it}p_{jt}; \tag{A.3}$$

$$\begin{aligned}[h_{it}]:\ \varphi_1h_{it}^{\frac{1}{\nu}}=\mu_{it}\Bigg[&-p_{Et}\,\iota_1\iota_0\left[\log(1+z_{it}w_th_{it})\right]^{\iota_1-1}\frac{z_tw_t}{1+z_tw_th_t}\\ &+(1-\tau^l)\lambda_t\left(z_{it}w_th_{it}\right)^{-\tau^l}z_{it}w_t\Bigg];\end{aligned} \tag{A.4}$$

$$[a_{i,t+1}]:\ \beta^t\mu_{it}=\beta^{t+1}\mathbb{E}_t\left[\mu_{i,t+1}\big(1+(1-\tau^a)r_{t+1}\big)+\frac{\partial T\left(a_{i,t+1}\right)}{\partial a_{i,t+1}}\cdot\mathbb{1}_{\{h_{it}=0\}}\right]; \tag{A.5}$$

$$[\mu_{1it}]:\ \sum\nolimits_j\Omega_j^{\frac{1}{\sigma}}\left(\frac{c_{ijt}}{\boldsymbol{x}_{it}^{\epsilon_j}}\right)^{\frac{\sigma-1}{\sigma}}=1; \tag{A.6}$$

$$[\mu_{it}]: \sum_j p_{jt}c_{ijt}+p_{Et}\,\iota_0\left[\log(1+z_{it}w_th_{it})\right]^{\iota_1}\cdot\mathbb{1}_{\{h_{it}>0\}}+a_{i,t+1}= \\ (1+(1-\tau^a)\,r_t)\,a_{it}+\lambda_t\left(z_{it}w_th_{it}\right)^{1-\tau^l}+T\left(a_{it}\right)\cdot\mathbb{1}_{\{h_{it}=0\}}. \tag{A.7}$$

From equation (A.3), we have

$$\mu_{1it}\cdot\frac{1-\sigma}{\sigma}=\mu_{it}\sum_j p_{jt}c_{ijt}=\mu_{it}Exp_{it}=\mu_{it}P_{it}\boldsymbol{x}_{it}; \tag{A.8}$$

$$\Rightarrow \mu_{1it}=\mu_{it}\frac{\sigma}{1-\sigma}Exp_{it}=\mu_{it}\frac{\sigma}{1-\sigma}P_{it}\boldsymbol{x}_{it}. \tag{A.9}$$

We can now substitute the expression for $\mu_{1it}$ from equation (A.9) into equation (A.3) and solve for the demand function of each item in the consumption basket:

$$c_{ijt}=\Omega_j\left(\frac{p_{jt}}{Exp_{it}}\right)^{-\sigma}\boldsymbol{x}_{it}^{\epsilon_j(1-\sigma)}. \tag{A.10}$$

Given the prices and demand functions of items in the consumption basket, we can derive the expenditure on the consumption basket:

$$Exp_{it}=\sum_j p_{jt}c_{ijt}; \tag{A.11}$$

$$\Rightarrow Exp_{it}=\left(\sum_j\Omega_j\left(p_{jt}\boldsymbol{x}_{it}^{\epsilon_j}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{A.12}$$

Thus, the price index of the household's consumption basket can be expressed as follows:

$$P_{it}=\frac{Exp_{it}}{\boldsymbol{x}_{it}}; \tag{A.13}$$

$$\Rightarrow P_{it}=\left(\sum_j\Omega_j\left(p_{jt}\boldsymbol{x}_{it}^{\epsilon_j-1}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{A.14}$$

Now, we can solve for $\mu_{it}$ by combining equations (A.2) and (A.9):

$$\mu_{it}=\frac{\boldsymbol{x}_{it}^{-\gamma}}{P_{it}}\cdot\frac{1}{\sum_j\Omega_j^{\frac{1}{\sigma}}\left(\frac{c_{ijt}}{\boldsymbol{x}_{it}^{\epsilon_j}}\right)^{\frac{\sigma-1}{\sigma}}\epsilon_j}; \tag{A.15}$$

$$\Rightarrow \mu_{it}=\frac{\boldsymbol{x}_{it}^{-\gamma}}{P_{it}}\cdot\frac{1}{\left(\frac{1}{P_{it}}\right)^{1-\sigma}\sum_j\Omega_j\left(p_{jt}\boldsymbol{x}_{it}^{\epsilon_j-1}\right)^{1-\sigma}\epsilon_j}; \tag{A.16}$$

$$\Rightarrow \mu_{it} = \frac{\boldsymbol{x}_{it}^{-\gamma}}{\left(\sum_j \Omega_j \left(p_{jt}\boldsymbol{x}_{it}^{\epsilon_j - 1}\right)^{1-\sigma}\right)^{\frac{\sigma}{1-\sigma}}} \cdot \frac{1}{\sum_j \Omega_j \left(p_{jt}\boldsymbol{x}_{it}^{\epsilon_j - 1}\right)^{1-\sigma} \epsilon_j}. \tag{A.17}$$

From equation (A.5), we can obtain the Euler equation:

$$\mu_{it} = \beta \mathbb{E}_t \left[ \mu_{i,t+1}(1 + (1-\tau^a) r_{t+1}) + \frac{\partial T\left(a_{i,t+1}\right)}{\partial a_{i,t+1}} \cdot \mathbb{1}_{\{h_{it}=0\}} \right]. \tag{A.18}$$

Substituting equation (A.17) into equation (A.4) yields household's labor supply allocation.

**Demand Estimation Equation.** Recall, household $i$'s equilibrium allocation for any good $j$:

$$c_{ijt} = \Omega_j \left(\frac{p_{jt}}{Exp_{it}}\right)^{-\sigma} \boldsymbol{x}_{it}^{\epsilon_j(1-\sigma)}. \tag{A.19}$$

Given the expression for $c_{ijt}$, we can obtain household $i$'s expenditure share of that good:

$$\omega_{ijt} \equiv \frac{c_{ijt} p_{jt}}{Exp_{it}} = \Omega_j \left(\frac{p_{jt}}{Exp_{it}}\right)^{1-\sigma} \boldsymbol{x}_{it}^{\epsilon_j(1-\sigma)}. \tag{A.20}$$

Therefore, the household's expenditure shares of a pair of goods, $j$ and $k$, satisfy:

$$\frac{\omega_{ijt}}{\omega_{ikt}} = \frac{\Omega_j}{\Omega_k} \left(\frac{p_{jt}}{p_{kt}}\right)^{1-\sigma} \boldsymbol{x}_{it}^{(\epsilon_j - \epsilon_k)(1-\sigma)}. \tag{A.21}$$

Equation (A.21) can also be written in log form:

$$\ln\left(\frac{\omega_{ijt}}{\omega_{ikt}}\right) = \ln\left(\frac{\Omega_j}{\Omega_k}\right) + (1-\sigma)\ln\left(\frac{p_{jt}}{p_{kt}}\right) + (\epsilon_j - \epsilon_k)(1-\sigma)\ln \boldsymbol{x}_{it}. \tag{A.22}$$

Now, using the log-linear nature of the demand system, the household's real consumption index at time $t$, $\boldsymbol{x}_{it}$, can be represented as a function of observables and preference parameters. In doing so, I can normalize $\epsilon_k = \Omega_k = 1$ without loss of generality and obtain:

$$\ln \boldsymbol{x}_{it} = \ln\left(\frac{Exp_{it}}{p_{kt}}\right) + \frac{1}{(1-\sigma)} \ln \omega_{ikt}. \tag{A.23}$$

By combining equations (A.22) and (A.23), we obtain

$$\begin{aligned} \ln\left(\frac{\omega_{ijt}}{\omega_{ikt}}\right) = (1-\sigma)\ln\left(\frac{p_{jt}}{p_{kt}}\right) + (1-\sigma)(\epsilon_j - \epsilon_k)\ln\left(\frac{Exp_{it}}{p_{kt}}\right) \\ + (\epsilon_j - \epsilon_k)\ln \omega_{ikt} + \ln\left(\frac{\Omega_j}{\Omega_k}\right). \end{aligned} \tag{A.24}$$

By incorporating, $\epsilon_k = \Omega_k = 1$, equation (A.24) can be written as follows:

$$\ln\left(\frac{\omega_{ijt}}{\omega_{ikt}}\right) = (1-\sigma)\ln\left(\frac{p_{jt}}{p_{kt}}\right) + (1-\sigma)(\epsilon_j - 1)\ln\left(\frac{Exp_{it}}{p_{kt}}\right) + (\epsilon_j - 1)\ln\omega_{ikt} + \underbrace{\ln\left(\Omega_j\right)}_{\text{constant}\equiv\zeta}. \tag{A.25}$$

In my demand estimation, I use the empirical counterpart of equation (A.25).

### *A.2. Firm Problem*

A representative firm in a perfectly competitive market produces non-energy goods and maximizes profits. With the output price normalized to 1, the profit maximization problem can be written as:

$$\max_{\{L_t, E_{F_t}, K_t\}} \Pi_t \equiv Y_t - R_t K_t - w_t L_t - p_{Et} E_{F_t}, \tag{A.26}$$

subject to

$$Y_t = \min\left[K_t^{\alpha} {L_t}^{1-\alpha}, \kappa A_{Et} E_{Ft}\right], \tag{A.27}$$

$$\kappa A_{Et} E_{Ft} \leq K_t^{\alpha} {L_t}^{1-\alpha}. \tag{A.28}$$

Let $\mu_t^F$ be the Lagrange multiplier. Then, the Lagrangian is given by

$$\mathcal{L}_t = \kappa A_{Et} E_{Ft} - R_t K_t - w_t L_t - p_{Et} E_{F_t} - \mu_t^F\left(\kappa A_{Et} E_{Ft} - K_t^{\alpha} {L_t}^{1-\alpha}\right). \tag{A.29}$$

Complementary slackness implies

$$\mu_t^F\left(\kappa A_{Et} E_{Ft} - K_t^{\alpha} {L_t}^{1-\alpha}\right) = 0. \tag{A.30}$$

The constraint always binds since firms do not rent capital, hire labor, or purchase energy without using it. The first order conditions with respect to $E_{Ft}$, $L_t$, and $K_t$ are given by

$$[E_{Ft}]: \ \kappa A_{Et} - p_{Et} - \mu_t^F \kappa A_{Et} = 0; \tag{A.31}$$

$$[L_t]: \ -w_t + (1-\alpha)\mu_t^F K_t^{\alpha} {L_t}^{-\alpha} = 0; \tag{A.32}$$

$$[K_t]: \ -R_t + \alpha \mu_t^F K_t^{\alpha-1} {L_t}^{1-\alpha} = 0. \tag{A.33}$$

From equation (A.31), we have

$$\mu_t^F = 1 - \frac{p_{Et}}{\kappa A_{Et}} \tag{A.34}$$

We can now solve for $w_t$ by substituting equation (A.34) into equation (A.32):

$$w_t = (1-\alpha)\left(1 - \frac{p_{Et}}{\kappa A_{Et}}\right)\left(\frac{K_t}{L_t}\right)^{\alpha}. \tag{A.35}$$

Similarly, we can solve for $R_t$ by substituting equation (A.34) into equation (A.33):

$$R_t = \alpha\left(1 - \frac{p_{Et}}{\kappa A_{Et}}\right)\left(\frac{K_t}{L_t}\right)^{\alpha-1}. \tag{A.36}$$

Combining equations (A.35) and (A.36) yield the capital-labor ratio in production:

$$\frac{K_t}{L_t} = \left(\frac{\alpha}{1-\alpha}\right)\left(\frac{w_t}{R_t}\right). \tag{A.37}$$

From equations (A.35) and (A.37), we can express $w_t$ in terms of the parameters and other factor prices:

$$w_t = (1-\alpha)\left[\alpha^{\alpha}\left(1 - \frac{p_{Et}}{\kappa A_{Et}}\right){R_t}^{-\alpha}\right]^{\frac{1}{(1-\alpha)}}. \tag{A.38}$$

## Appendix B: Data Description

### *B.1. U.S. Energy Information Administration Data*

The U.S. Energy Information Administration (EIA) provides information on energy consumption and expenditures since 1970, categorized into four broad sectors: residential, commercial, industrial, and transportation.

### *B.2. Consumer Expenditure Survey*

The source of the household consumption expenditure data is the Consumer Expenditure Survey (CEX). It is a nationally representative survey conducted by the Bureau of Labor Statistics (BLS). It consists of two separate surveys: the Interview Survey and the Diary Survey. The Interview Survey is a quarterly rotating panel of U.S. households, where each household is interviewed about their expenditures for up to four consecutive quarters. These interviews document expenditures across detailed categories over the preceding

three months. The final interview records income-related details from the previous twelve months, aligning with the period corresponding to expenditures. On the other hand, the Diary Survey requires households to record their daily expenses on small yet frequently purchased items (e.g., food, beverages, personal care products) over two weeks while not covering infrequently purchased items. All variables in both surveys are recorded at the household level. The surveys also record household demographic information, including the number of household members, the number of household earners, and the reference member's age, education, and employment status.

For the baseline analysis, I use data spanning from 1999 to 2013, restricting the sample to households with reference persons aged between 25 and 64 who participated in at least four interviews and are complete income reporters. I choose 2013 as the final year of my sample due to the termination of the variable in the CEX that represents complete income information. On the other hand, I choose 1999 as the starting year to maintain consistency with my quantitative analysis. To estimate parameters related to household consumption preferences, I use a 'Hausman' relative-price instrument, which is constructed by combining CEX expenditure data with disaggregated regional quarterly price series from the BLS's Urban Consumer Price Index (CPI-U), which started in 1999.

The dataset is constructed following the methodology of Aguiar and Bils (2015), which closely aligns with Krueger and Perri (2006) and Heathcote, Perri, and Violante (2010). I categorize items in household consumption baskets listed in the CEX into three broad groups: (i) commuting energy, which includes energy commodities consumed as fuel for personal vehicles for commuting to work; (ii) residential energy, which includes energy commodities used for purposes other than commuting to work; and (iii) non-energy.

### *B.3. Panel Study of Income Dynamics*

I use data from the Panel Study of Income Dynamics (PSID) to compute empirical moments related to household wealth, earnings, and employment. It is a longitudinal study of a sample of U.S. households originally designed to study income and poverty dynamics. For this purpose, the sample is drawn from two independent sub-samples: an over-sample

of approximately 2,000 poor families selected from the Survey of Economic Opportunities (SEO) and a nationally representative sample of about 3,000 families designed by the Survey Research Center (SRC) at the University of Michigan. Starting in 1968, the PSID is the longest-running representative U.S. household panel. It was conducted annually until 1997 and has become biennial since then.

The PSID data files provide a wide variety of information for U.S. households, with substantial detail on income sources and amounts, employment status, wealth, family composition, and residential location. For consistency in my study, I use the biennial waves of the PSID from 1999 to 2013 for household heads aged between 25 and 64.

## APPENDIX C: DEMAND ESTIMATION

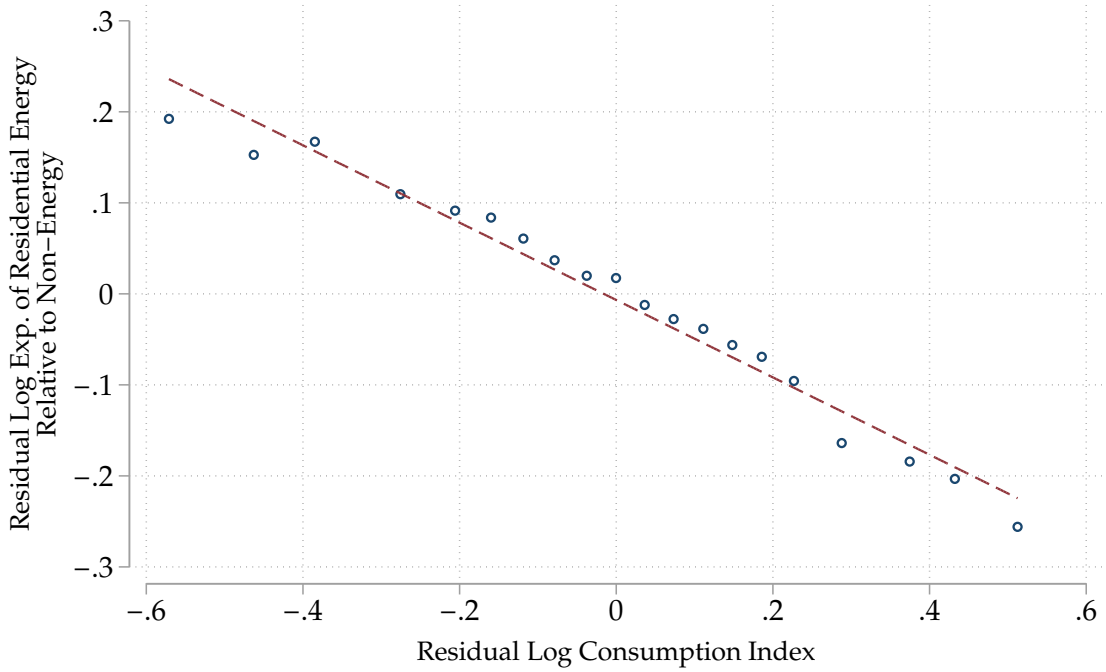
I estimate the demand system using household-level quarterly expenditure data from the CEX, supplemented with the BLS's disaggregated regional quarterly price series (CPI-U). The estimation approach is based on the generalized method of moments (GMM) and follows the methodology outlined in Comin, Lashkari, and Mestieri (2021). To obtain the estimating equation, using equation (A.10), I first write down an equation in terms of a household's expenditure shares on energy ($\omega_{iERt}$) and non-energy ($\omega_{iCt}$) goods:

$$\ln\left(\frac{\omega_{iERt}}{\omega_{iCt}}\right) = (1-\sigma)\ln\left(\frac{p_{Et}}{p_{Ct}}\right) + (1-\sigma)(\epsilon_{ER}-1)\ln\left(\frac{Exp_{it}}{p_{Ct}}\right) + (\epsilon_{ER}-1)\ln\omega_{iCt} + \underbrace{\ln(\Omega_{ER})}_{\text{constant}\equiv\zeta}, \tag{C.1}$$

where without loss of generality, I normalize $\epsilon_C = \Omega_C = 1$. The right- and left-hand side variables in the above equation are observable in the data. I now can write an empirical counterpart of equation (C.1) as:

$$\ln\left(\frac{\omega_{iERt}}{\omega_{iCt}}\right) = (1-\sigma)\ln\left(\frac{p_{iEt}}{p_{iCt}}\right) + (1-\sigma)(\epsilon_{ER}-1)\ln\left(\frac{Exp_{it}}{p_{iCt}}\right) + (\epsilon_{ER}-1)\ln\omega_{iCt} + \zeta_{iER} + \varepsilon_{iERt}, \tag{C.2}$$

where $p_{iERt}$ and $p_{iCt}$ are, respectively, the prices of energy and non-energy goods faced by household $i$ at time $t$. Each of these prices is constructed by taking the household




*Source*: CEX

**FIGURE C.1**
PARTIAL CORRELATION OF THE LOG CONSUMPTION INDEX AND LOG EXPENDITURE SHARE OF ENERGY RELATIVE TO NON-ENERGY

*Note.* The figure depicts the (binned) residuals corresponding to the average value of 20 equal-sized bins of the data. The red line depicts the linear regression between the residualized variables.

expenditure-weighted average log prices of all sub-components within the respective consumption category. Since expenditure weights are household-specific, this allows me to (imperfectly) account for the fact that each category's effective price may differ across households. $\zeta_{iER}$ accounts for relative taste parameter, $\zeta_{iER} \equiv \ln(\Omega_{iER}/(\Omega_{iC} = 1))$, and $\varepsilon_{iERt}$ represents the error term.

Following Comin, Lashkari, and Mestieri (2021), I also impose two additional assumptions. First, the household level taste-shocks are linear functions of observables $\zeta_{iER} = \beta' \mathbf{Z}_i + \nu_{ERr}$. The assumption imposes the constraint that the cross-household heterogeneity in time-invariant taste parameter can be fully explained as a linear function of the vector $\mathbf{Z}_i$ of household characteristics (age, household size, and the number of earners dummies) and consumption-category×region fixed effects. The second assumption is that the error term,

$\varepsilon_{iERt}$, may contain common consumption-category×time fixed effects across households, $\varepsilon_{iERt} = \nu_{ERt} + \tilde{\varepsilon}_{iERt}$. This assumption allows for a dyad of consumption-category×time fixed effects to absorb potential aggregate consumption shocks.

To deal with potential measurement error and endogeneity issues, I instrument the observed measures of household expenditures and relative prices. First, I instrument quarterly household expenditures with the annual household income after taxes and the income quintile of the household, similar to Aguiar and Bils (2015) and Comin, Lashkari, and Mestieri (2021). The instrument captures the permanent household income and is correlated with household expenditures without being affected by transitory measurement error in total spending. Second, I instrument household relative prices with a Hausman-style relative-price instrument, as in Comin, Lashkari, and Mestieri (2021). The price of each sub-component in the relative-price instrument is constructed in two steps. In the first step, for each sub-component of a consumption category, I compute the average price across regions, excluding the own region. Next, the price of each consumption category for a region is constructed using the region-specific expenditure shares of each sub-component as weights. This price instrument captures the common trend in U.S. consumption prices and addresses endogeneity concerns arising from regional shocks.

In order to validate the demand estimation presented in Table 1, I compare the structurally estimated expenditure elasticities with their reduced-form counterparts.[21] For the reduced-form estimation, I follow the approach proposed by Aguiar and Bils (2015). Denoting a household by $i$, I estimate expenditure elasticity of consumption good $j$, $\eta_j$, as:

$$\ln\left(\frac{\mathbb{X}^i_{jt}}{\overline{\mathbb{X}}_{jt}}\right) = \alpha_{jtr} + \eta_j \ln Exp^i_t + \mathbf{\Gamma}_j \mathbf{Z}^i + u^i_{jt}, \qquad j = \{ER, C\}, \tag{C.3}$$

where $\mathbb{X}^i_{jt}$ is the expenditure on good $j$ from household $i$ during quarter $t$, $\overline{\mathbb{X}}_{jt}$ denotes the average expenditure on good $j$ across households during quarter $t$, $\alpha_{jtr}$ captures time and region fixed effects, $Exp^i_t$ represents total quarterly expenditure of household $i$, $\mathbf{Z}^i$ is

21. The structural estimation uses $\eta_j = \sigma + (1-\sigma)\left(\epsilon_j/\bar{\epsilon}\right)$, where $\bar{\epsilon}$ is the weighted average of non-homotheticity parameters, with weights corresponding to average consumption expenditure shares.

**TABLE C.1**
EXPENDITURE SHARES AND EXPENDITURE ELASTICITIES OF CONSUMPTION CATEGORIES

| Consumption Category | CE Share (in Percentage) | Nonhomothetic CES | | Reduced-Form |
|---|---|---|---|---|
| | | $\epsilon_j$ | $\eta_j$ | $\eta_j$ |
| Energy | 7.20 | 0.346*** (0.020) | 0.521 | 0.466*** (0.007) |
| Non-Energy | 92.80 | 1.00 (-) | 1.037 | 0.989*** (0.005) |

*Note*. The structural estimation of $\eta_j$ uses $\sigma = 0.239$ as the elasticity of substitution between energy and non-energy consumption. All regressions include household controls: age (25-37, 38-50, 51-64), household size ($\leq$2, 3-4, 5+), and the number of earners (1, 2+). Standard errors clustered at the household level are shown in parentheses. *** indicates significance at the 1% level. CE = Expenditure on Consumption Basket.

a vector of demographic controls (age, household size, and number of earners), and $u^i_{jt}$ is an error term. To address potential measurement error issues, I follow Aguiar and Bils (2015) and instrument total expenditures with yearly income after taxes and the income quintile. The rationale is that total expenditure reflects permanent income and thus is correlated with current income. Table C.1 presents the expenditure elasticities obtained from the reduced-form and the structural estimation.

## APPENDIX D: SOLUTION ALGORITHM

I begin by describing the algorithm for solving the steady state equilibrium of my model. Next, I describe how the calibration process outlined in Section 5 is implemented. Lastly, I explain the algorithm for solving the transition dynamics.

### *D.1. Steady State*

1. Construct asset and labor productivity grids:
   (a) I use 650 points for the asset grid, putting more points close to the borrowing constraint.
   (b) I discretize the labor productivity process and approximate the Markov transition matrix using the Rouwenhorst (1995) method. In this step, I use 16 grid points, placing the outermost values at three standard deviations from the mean. In the next step, when endogenous parameters are set, I add an extreme produc-

tivity state, $z_{max}$, along with the probability of transitioning to $z_{max}$ from other states and the probability of remaining there. I assume that $z_{max}$ is only reachable from the upper half of the normal productivity states with the same probability.

2. Make a guess for the set of endogenous parameters.
3. Make a guess for the fiscal parameter $\lambda$ that balances the government budget.
4. Make a guess for the steady state real rate of return, $r$, and solve for wage rate, $w$, using equation (A.38).
5. Solve for the household value function and obtain policy functions:
   (a) Initialize the value function $V_0(a, z)$.
   (b) Solve the consumption-saving problem for each employment status to obtain $V^E(a, z)$ and $V^U(a, z)$.
   (c) Get $V_1(a, z) = \max\{V^E(a, z), V^U(a, z)\}$.
   (d) Check if $\max|V_1(a, z) - V_0(a, z)| < \epsilon$. If this condition is met, the value function is obtained. Otherwise, update the initial value function by setting $V_0(a, z) = V_1(a, z)$ and repeat steps 5(b)-5(d) until the convergence criterion is met. To gain computational speed, I use Howard's improvement step.
   (e) After obtaining the value function, solve for the household policy functions $E_T(a, z)$, $E_R(a, z)$, $C(a, z)$, $h(a, z)$, $a'(a, z)$, and $T(a, z)$.
6. Given the household policy function $a'(a, z)$ and the transition probability matrix obtained in step 1(b), find the invariant distribution $\Gamma^\star(a, z)$.
7. Given the household asset holdings $a(a, z)$ and the invariant distribution $\Gamma^\star(a, z)$, compute the aggregate supply of capital $K_s = \int a(a, z)\, d\Gamma$ and labor $L_s = zh(a, z)\, d\Gamma$.
8. In equation (A.36) apply the labor market clearing condition, $L_d = L_s$, and solve for the aggregate demand for capital, $K_d$.
9. Check the capital market clearing condition. If the market clears, the steady state real rate of return is obtained. Otherwise, return to step 4, update the guess for $r$, and repeat the process until the capital market clearing condition is met. I use Brent's root finding method to solve for the value of $r$ that clears the market.

10. Check if the government budget in equation (11) is balanced. If it is balanced, the steady state equilibrium for the given set of parameters is obtained. If not, return to step 3, update the guess for $\lambda$, and repeat the process until the government budget is balanced. For this step, I also use a root finding algorithm.

### *D.2. Calibration*

First, solve for the steady state equilibrium given a set of endogenous parameters using the algorithm described in Section D.1. Next, compute targeted moments from the simulated model data. Then, check if the residual sum of squares between the model moments and their corresponding empirical moments meets the convergence criterion. If the criterion is met, the calibration process is complete. Otherwise, return to step 2 in Section D.1, update endogenous parameters, and repeat the process until the convergence criterion is met.

### *D.3. Transition Dynamics*

Assume that after experiencing an energy price shock, the economy converges to a new steady state by period $T$. Since I consider a one-time MIT shock, the path for the energy price is determined after the shock.

1. Solve for the final steady state using the algorithm outlined in Section D.1.
2. Guess a sequence of real rates of return $\{r_t\}_{t=1}^{T-1}$.
3. Solve for the respective wage rates $\{w_t\}_{t=1}^{T-1}$ using equation (A.38).
4. Make a guess for the maximum possible lump-sum transfer a household can receive in each period over the transition path $\{T_t\}_{t=1}^{T-1}$.
5. Guess a sequence of government budget balancing parameter $\{\lambda_t\}_{t=1}^{T-1}$.
6. Solve the value function and policy functions backward from $t = T-1, \cdots, 1$. Start this step by setting $V_T(a_T, z_T)$ equal to the value function obtained in the final steady state in step 1.
7. Starting from the initial steady state distribution $\Gamma^\star$, simulate the distribution $\Gamma$ forward from $t = 1$ to $t = T-1$ using the policy function $a'(a, z)$ and idiosyncratic labor productivity Markov transition matrix obtained in step 1(b) of Section D.1.

8. Check if the government budget is balanced in each period. If it is balanced, proceed to the next step. Otherwise, update the sequence $\{\lambda_t\}_{t=1}^{T-1}$ using a convex combination of the current and implied sequence of $\lambda$, then return to step 6 and repeat the process until the convergence criterion is met. In practice, I compare the current sequence of $\lambda$ with the implied sequence to check for convergence.
9. Check if the government spending on lump-sum transfer to GDP ratio is constant in each period. If it is constant, proceed to the next step. Otherwise, update the sequence $\{T_t\}_{t=1}^{T-1}$ using a convex combination of the current and implied sequence of $T$, then return to step 5 and repeat the process until the convergence criterion is met.
10. Check if the difference between the current and implied sequences of the real rate of return is less than the specified tolerance level. If so, the solution is complete. Otherwise, update the sequence $\{r_t\}_{t=1}^{T-1}$ using a convex combination of the current and implied sequence of $r$, then return to step 3 and repeat the process until the convergence criterion is met.

## APPENDIX E: AN EXAMPLE OF ENERGY PRICE SHOCK IMPACT

In this section, I empirically examine the impact of an oil price shock on consumption. The focus on oil price shock stems from two main reasons. First, there exist well-identified instruments for oil price shocks. Second, oil price shocks are one of the main drivers of broader energy price shocks. I instrument oil price shock using the oil supply news shock of Känzig (2021). However, I abstract from using the news shock as a direct proxy for energy price shock due to potential weak instrument issues. This concern stems from the fact that these news shocks only explain a small fraction of the oil price fluctuations.

For the application, I begin by replicating the baseline Structural Vector Autoregression Instrumental Variable (SVAR-IV) model featured in Känzig (2021).[22] Following that model,

22. An alternative approach would be directly estimating the dynamic causal effects using local projections. However, applying it in this context is challenging due to the power problem of the instrument (see Nakamura and Steinsson, 2018). Intuitively, macroeconomic variables several periods out in the future are hit by numerous other shocks. Additionally, the oil price is a highly volatile variable, and the oil supply surprises account only for a small part of the price fluctuations, rendering the signal-to-noise ratio low, making it challenging to estimate the macroeconomic effects directly.

I consider a 12-lag log-level reduced-form VAR, which includes a vector $\mathbf{y}_t^{oil}$ of six variables: real oil price, world oil production, world oil inventories, world industrial production, U.S. industrial production, and U.S. consumer price index (CPI). I then use the Känzig (2021) oil supply surprise series—variation in oil futures prices around the Organization of the Petroleum Exporting Countries (OPEC) production announcements—as an external instrument to identify the column of the VAR impact matrix corresponding to the oil supply news shock. Finally, the oil supply news shock is identified under invertibility using the procedure in Stock and Watson (2018).

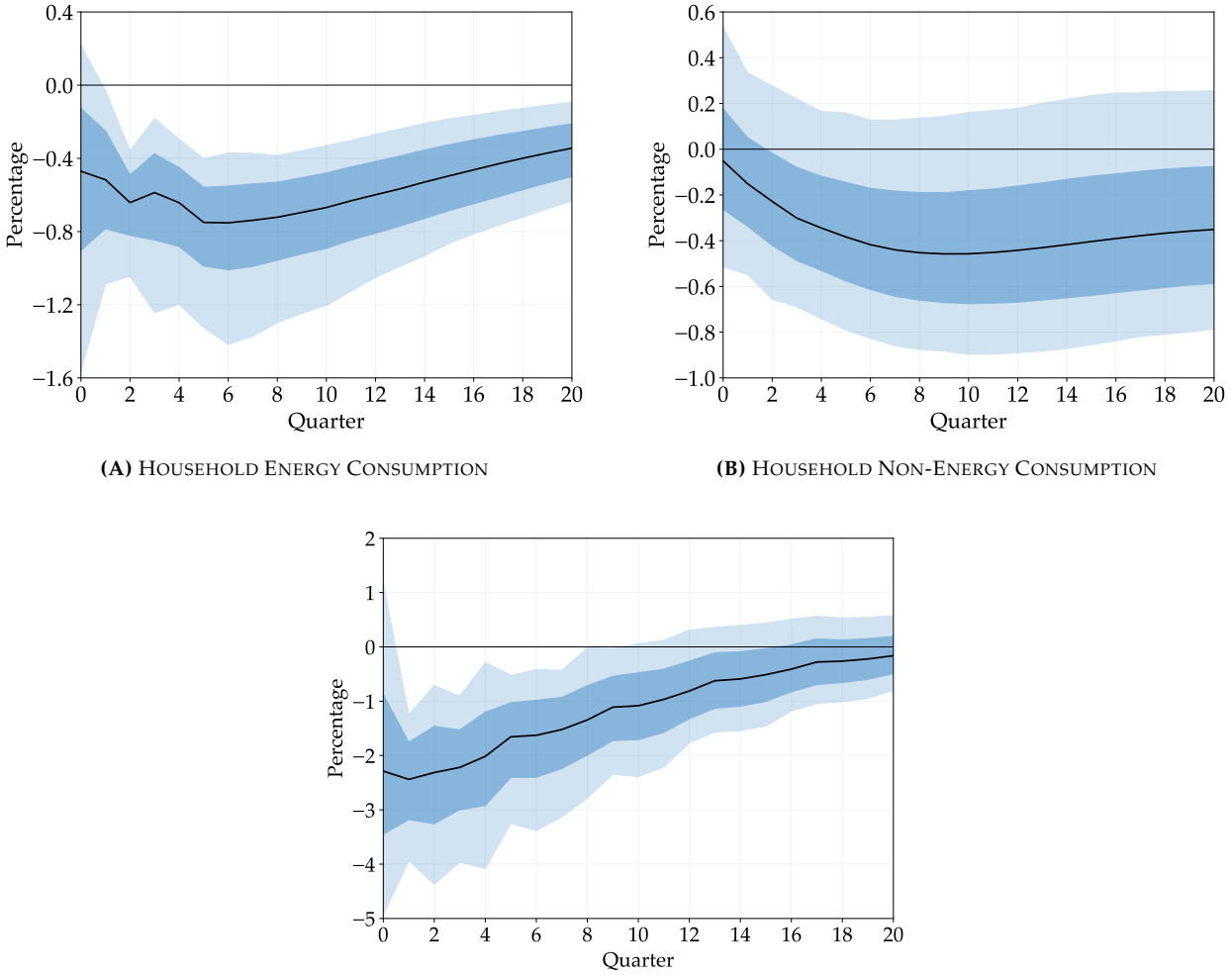
For the six endogenous variables in $\mathbf{y}_t^{oil}$, I use quarterly data from 1974:Q1 to 2017:Q4. Given the reduced form VAR parameters and instrument, a shorter sample from 1983:Q2 to 2017:Q4, for which period the instrument is available, is used to identify the oil supply news shock.[23] Given the strong correlation of these news shocks with the oil price series and their exogeneity to the U.S. economy, they are assumed to satisfy both the relevance and the exclusion restrictions. In addition, as suggested in Montiel Olea, Stock, and Watson (2021), an $F$-test in the first-stage regression of the oil price residual from the VAR on the instrument eliminates concerns of a weak instrument problem.

In the following step, I use the estimated oil supply news shock $z_t^{shock}$ as an "internal instrument" in separate recursive SVAR models for each of the outcome variables and estimate their corresponding impulse responses to an oil price shock:

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_{12}\mathbf{y}_{t-12} + \mathbf{H}\boldsymbol{\epsilon}_t \tag{E.1}$$

where $\mathbf{y}_t = [z_t^{shock}, \mathbf{y}_t^{oil}, y_t^i]'$, $y_t^i$ is the $i^{\text{th}}$ outcome variable, $\mathbf{b}$ is a vector of constants, and $\mathbf{B}_1 \cdots \mathbf{B}_{12}$ are coefficient matrices. From the "internal instrument" recursive causal ordering, the first column of $\mathbf{H}$, denoted as $\mathbf{H}_1$, identifies the impact response (i.e., the response at time horizon $th = 0$) of the oil supply news shock. I then store the element of $\mathbf{H}_1$ corresponding to the response of outcome variable $y_t^i$ as $\mathbf{IR}_0^i$. The impulse responses for subsequent horizons $\mathbf{IR}_{th>0}^i$ can be estimated by propagating the shock through the VAR model.

23. See Känzig (2021) for details.




**(A)** HOUSEHOLD ENERGY CONSUMPTION

**(B)** HOUSEHOLD NON-ENERGY CONSUMPTION

**(C)** FIRM ENERGY CONSUMPTION

**FIGURE E.1**
IMPULSE RESPONSES OF HOUSEHOLD ENERGY, NON-ENERGY CONSUMPTION, AND FIRM ENERGY CONSUMPTION TO AN OIL PRICE SHOCK

*Note.* The figure shows the impulse responses of household energy consumption (Panel A), non-energy consumption (Panel B), and firm energy consumption (Panel C) to an inflationary oil supply news shock of Känzig (2021). The shock is normalized to increase the real price of oil by 10% on impact, equivalent to one standard deviation increase in the real price of oil. The solid black lines represent the point estimates, while the shaded regions denote the 68 and 90 percent confidence bands based on 10,000 bootstrap replications.

**Consumption Response.** Figure E.1 shows that an inflationary oil price shock significantly impacts both household and firm energy consumption.[24] An inflationary oil price shock leads to a reduction in household energy, non-energy consumption, and firms' energy consumption. Although the response of household non-energy consumption is slightly less

24. Firm energy consumption includes energy consumption of the commercial and industrial sectors, as reported by the U.S. EIA.

precisely estimated, the point estimates clearly indicate a negative impact. Given the variations in household expenditure shares on energy across income groups, these impulse responses suggest that an energy price shock may have considerable distributional implications. However, the lack of disaggregated data for a long time series makes it challenging to precisely estimate the responses of such shocks for different income groups empirically.

## APPENDIX F: ADDITIONAL TABLES AND FIGURES

**TABLE F.1**
DEMAND ESTIMATION: COMBINING RESIDENTIAL AND COMMUTING ENERGY INTO A SINGLE ENERGY GOOD

| Parameter | (1) | (2) | (3) |
|---|---|---|---|
| $\sigma$ | 0.237*** | 0.264*** | 0.239*** |
| | (0.014) | (0.013) | (0.019) |
| $\epsilon_E$ | 0.368*** | 0.365*** | 0.383*** |
| | (0.015) | (0.015) | (0.017) |
| Region FE | $\mathcal{X}$ | ✓ | ✓ |
| Year × Quarter FE | $\mathcal{X}$ | $\mathcal{X}$ | ✓ |

*Note*. All regressions include household controls: age (25-37, 38-50, 51-64), household size ($\leq$2, 3-4, 5+), and the number of earners (1, 2+). Standard errors clustered at the household level are shown in parentheses. The number of observations is 130,132 in all regressions. *** indicate significance at the 1% level.

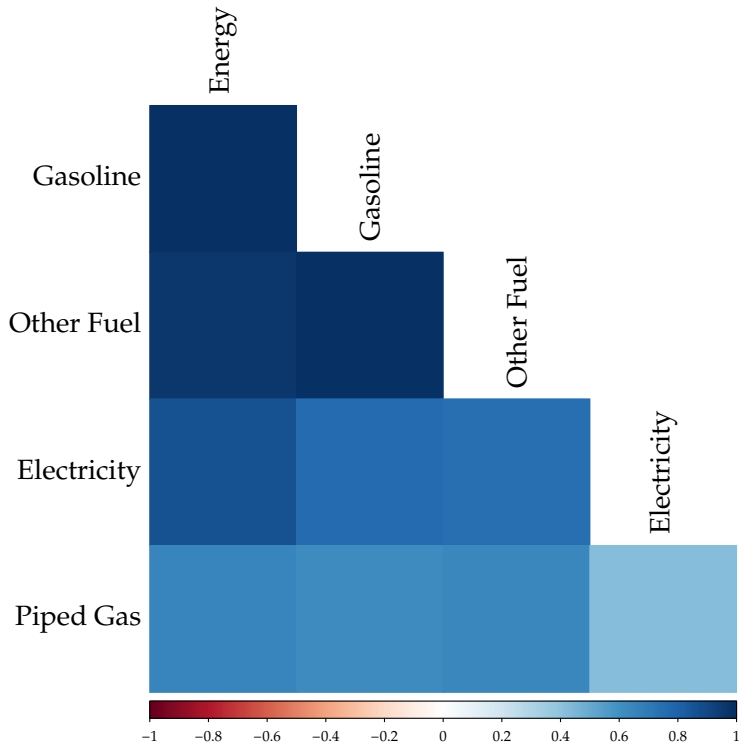



**FIGURE F.1**
CORRELATION MATRIX OF CPIS OF DIFFERENT ENERGY GOODS

*Note.* The figure shows the correlations among the CPIs of different final-use energy goods. *Energy CPI* is the weighted CPI of all final-use energy goods in the household consumption basket.

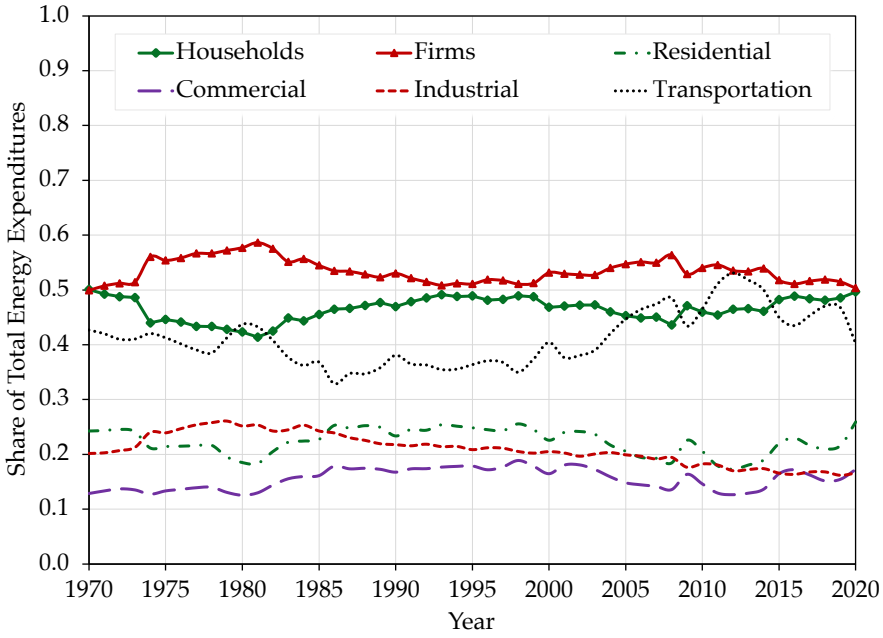



**FIGURE F.2**
PATTERNS OF ENERGY CONSUMPTION EXPENDITURES

*Note.* The figure shows historical patterns of energy consumption expenditures in the U.S., represented as a share of total energy expenditures.

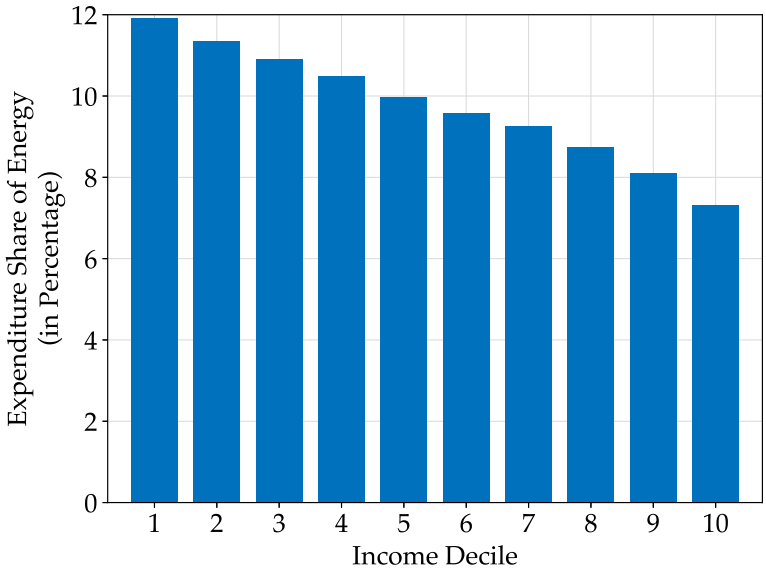



**FIGURE F.3**
DISTRIBUTION OF HOUSEHOLD EXPENDITURE SHARE ON ENERGY

*Note.* The figure plots the household energy expenditure shares across income deciles using the quarterly waves of CEX from 1999 to 2013. It includes all forms of household energy spending, such as electricity, piped gas, gasoline, and other types of fuel oil.

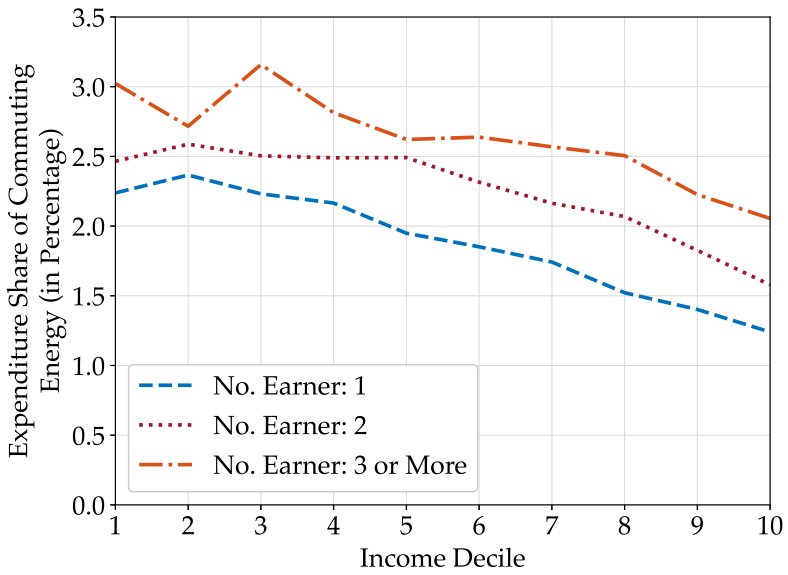
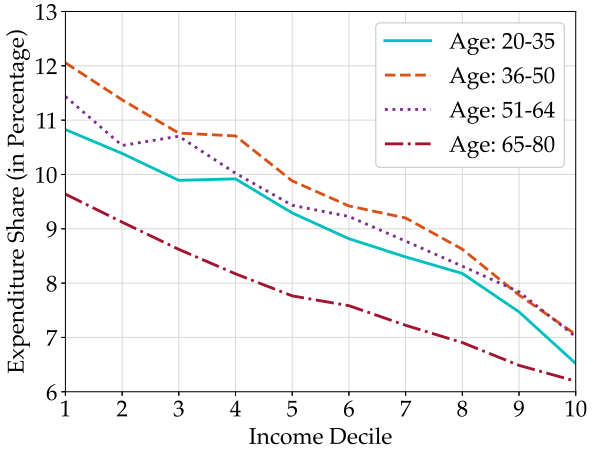
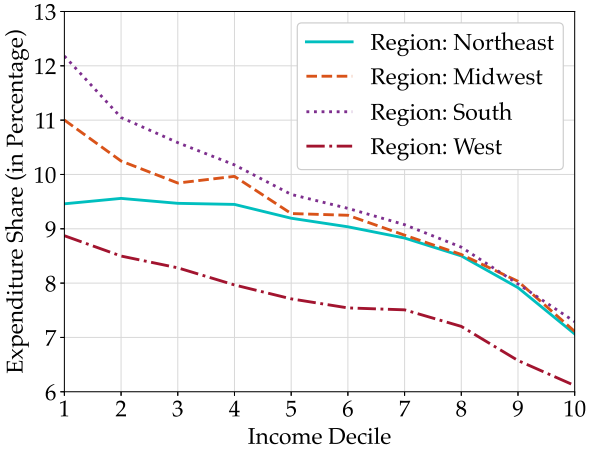



**FIGURE F.4**
DISTRIBUTION OF HOUSEHOLD EXPENDITURE SHARE ON COMMUTING ENERGY BY NUMBER OF EARNERS

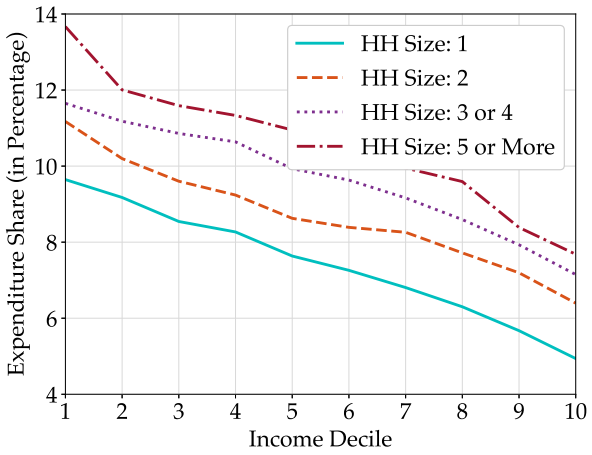
*Note.* The figure plots the household expenditure shares on commuting energy across income deciles by the number of earners in a household, using data from the quarterly waves of the CEX from 1994 to 2019. *Commuting energy* refers to the energy used to commute to work.



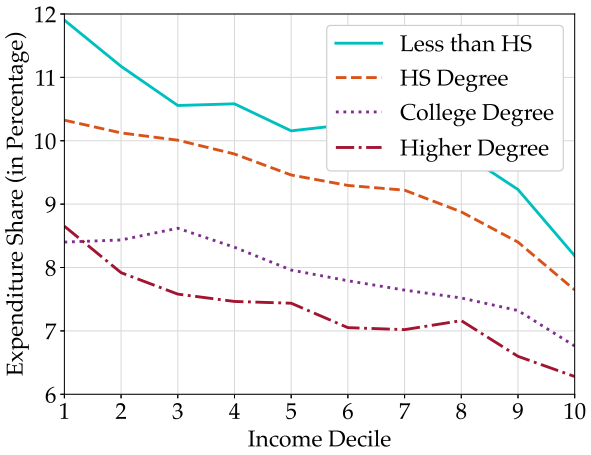

**(A)** ENERGY EXPENDITURE SHARE (BY AGE GROUP)




**(B)** ENERGY EXPENDITURE SHARE (BY REGION)



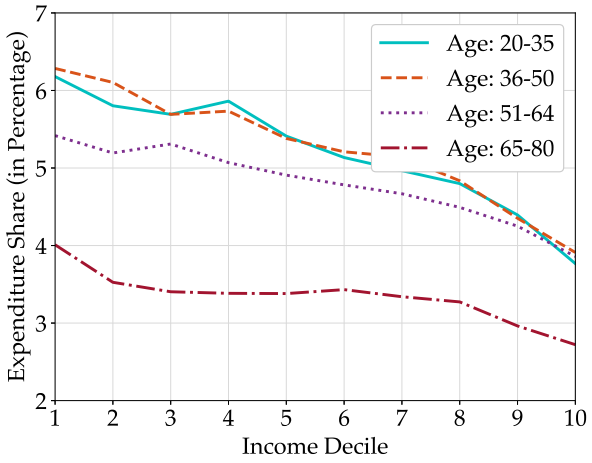

**(C)** ENERGY EXPENDITURE SHARE (BY HOUSEHOLD SIZE)



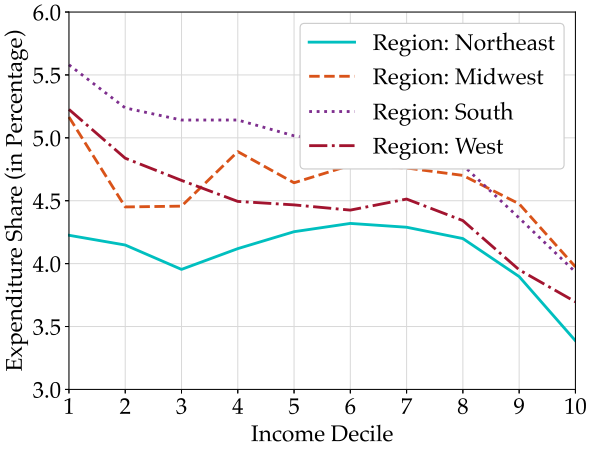

**(D)** ENERGY EXPENDITURE SHARE (BY EDUCATION GROUP)

**FIGURE F.5**
EXPENDITURE SHARE ON ENERGY BY DEMOGRAPHICS

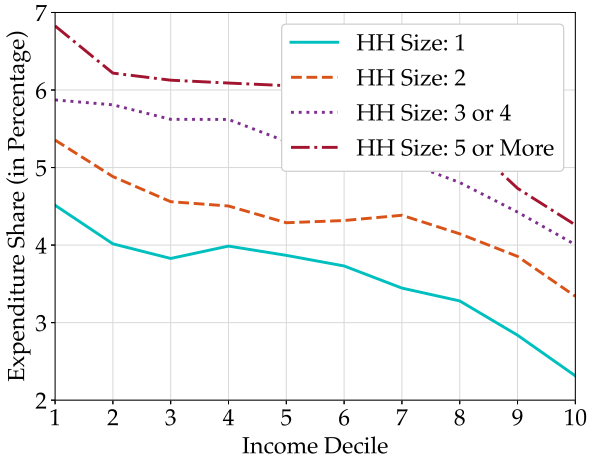
*Note.* The figure plots the household energy expenditure shares across income deciles by different demographic groups—age, region, household size, and education level—using the quarterly waves of CEX from 1994 to 2019. It includes all forms of household energy spending, such as electricity, piped gas, gasoline, and other types of fuel oil.



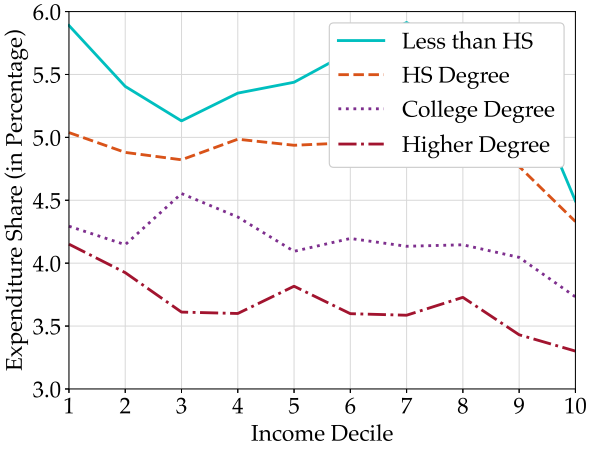

**(A)** GASOLINE EXPENDITURE SHARE (BY AGE GROUP)




**(B)** GASOLINE EXPENDITURE SHARE (BY REGION)



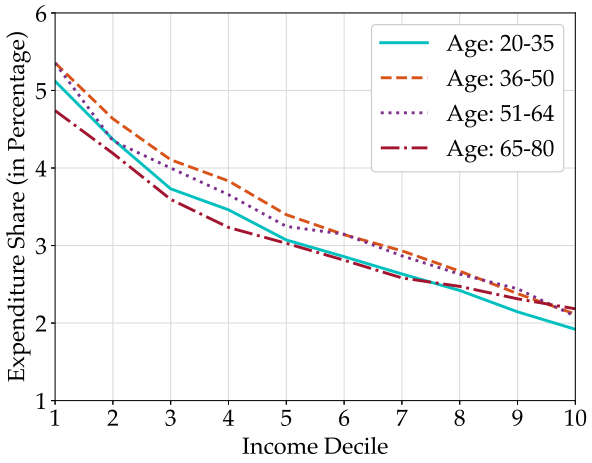

**(C)** GASOLINE EXPENDITURE SHARE (BY HOUSEHOLD SIZE)



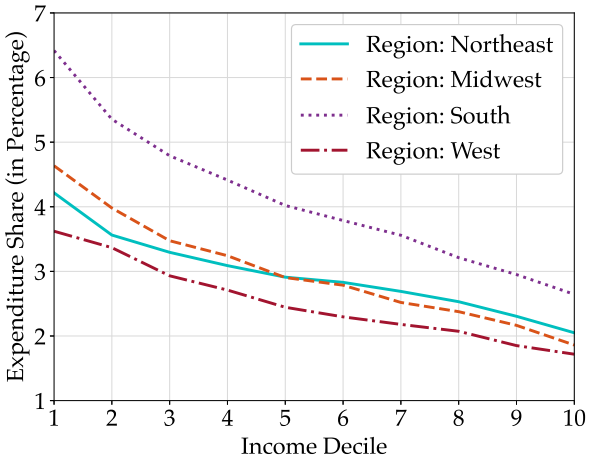

**(D)** GASOLINE EXPENDITURE SHARE (BY EDUCATION GROUP)

**FIGURE F.6**
EXPENDITURE SHARE ON GASOLINE BY DEMOGRAPHICS

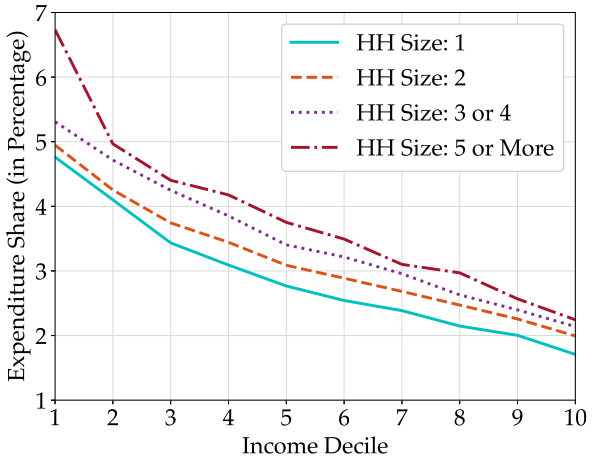
*Note.* The figure plots the household gasoline expenditure shares across income deciles by different demographic groups—age, region, household size, and education level—using the quarterly waves of CEX from 1994 to 2019.



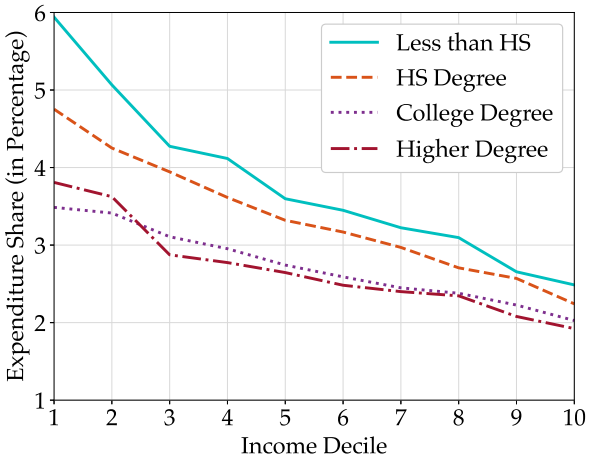

**(A)** ELECTRICITY EXPENDITURE SHARE (BY AGE GROUP)




**(B)** ELECTRICITY EXPENDITURE SHARE (BY REGION)



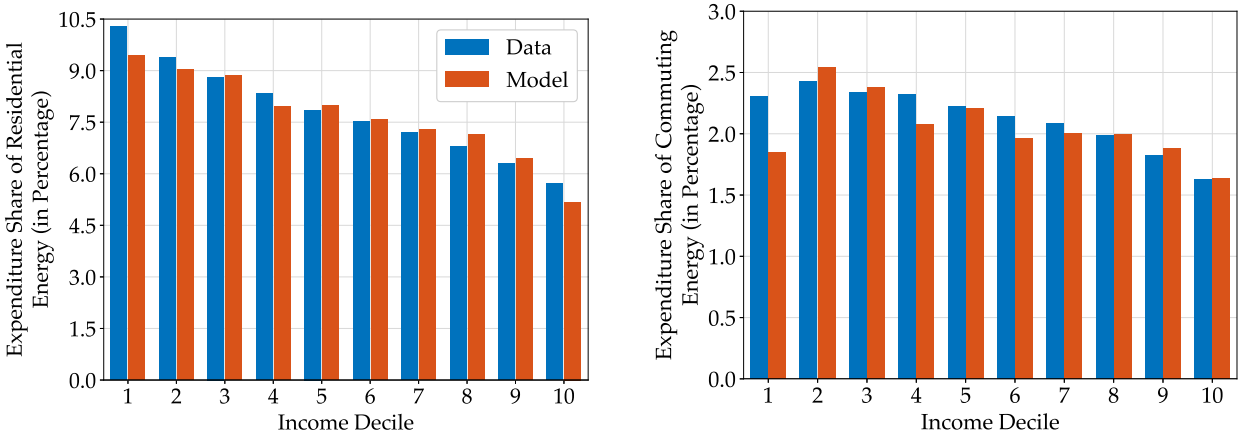

**(C)** ELECTRICITY EXPENDITURE SHARE (BY HOUSEHOLD SIZE)




**(D)** ELECTRICITY EXPENDITURE SHARE (BY EDUCATION GROUP)

**FIGURE F.7**
EXPENDITURE SHARE ON ELECTRICITY BY DEMOGRAPHICS

*Note.* The figure plots the household electricity expenditure shares across income deciles by different demographic groups—age, region, household size, and education level—using the quarterly waves of CEX from 1994 to 2019.




**(A)** DISTRIBUTION OF EXPENDITURE SHARE ON RESIDENTIAL ENERGY

**(B)** DISTRIBUTION OF EXPENDITURE SHARE ON COMMUTING ENERGY

**FIGURE F.8**
DISTRIBUTIONS OF HOUSEHOLD EXPENDITURE SHARE ON RESIDENTIAL AND COMMUTING ENERGY – MODEL VS. DATA

*Note.* The figure plots the distributions of household expenditure shares for residential (Panel A) and commuting (Panel B) energy consumption in the model and the data. The empirical moments are calculated using the quarterly waves of the CEX from 1999 to 2013 for households with reference persons aged 25-64 who participated in at least four interviews and are complete income reporters.