Commuting, Home Utilities, and Production: The Distributional Effects of Energy Price Shocks*

Mehedi Hasan Oni†

July 2024

Abstract

Energy price shocks are large and persistent relative to other price shocks. How do these shocks affect households across different income groups? To quantify the welfare effects of energy price shocks, I develop a heterogeneous-agent incomplete market model featuring non-homothetic consumption preferences, commuting costs, and energy as a factor of production for non-energy goods, taking the energy price as exogenous. A calibrated version of the model successfully reproduces many salient features of United States data, including the cross-sectional distributions of employment, income, wealth, and expenditure shares on energy consumption for both commuting and residential utilities. Quantitatively, I find that an inflationary energy price shock similar to the one in 2021 results in disproportionate welfare losses across income groups, with the bottom quintile losing almost twice as much as the top quintile in terms of consumption on impact. I also show that while work from home opportunity exacerbates consumption inequality, targeted transfer helps to mitigate it.

Keywords: Energy Price Shock; Inequality; Commuting Cost; Work from Home.

JEL Codes: D63, E21, E30, Q43.

*I am grateful to German Cubas, Vegard Nygaard, Bent Sørensen, and Dietrich Vollrath for invaluable comments and continuous guidance. I would also like to thank Nuray Akin, Xavier Bautista, Jose Mota, David Papell, Raul Santaeulalia-Llopis, Pedro Silos, Mitchell VanVuren, Michael Waugh, and participants at the UH Macroeconomics and Graduate Student Workshops, Özyeğin University, Istanbul Technical University, The University of Southern Mississippi, 2024 North American Summer Meeting of the Econometric Society, Fall 2023 Midwest Macro Meeting, and 2023 Texas Macro Job Candidate Conference for useful comments and suggestions. All errors herein are my own.

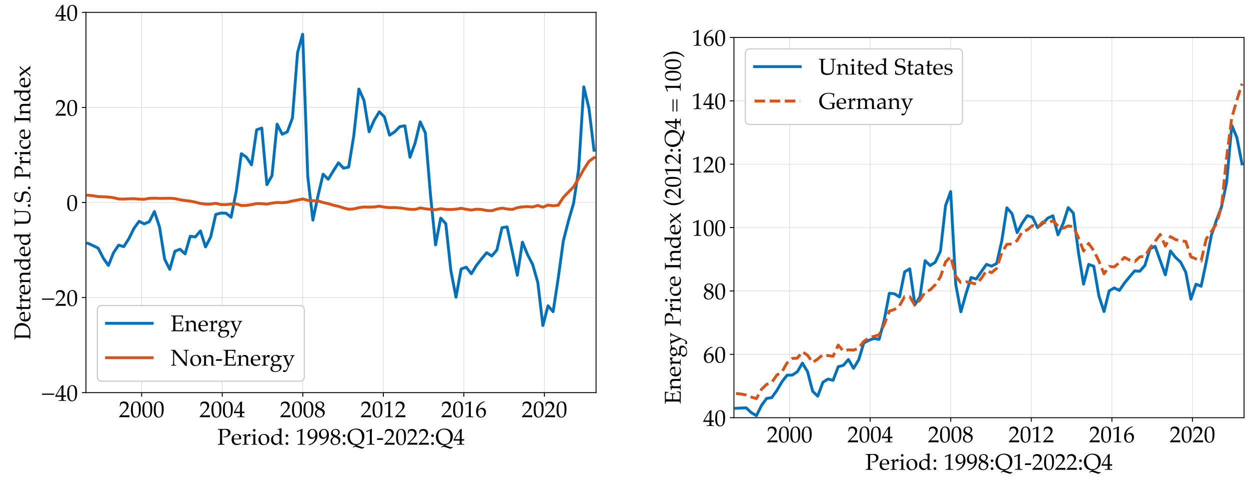
†Department of Economics, University of Houston, Houston, Texas, United States. E-mail: mhoni.acad@gmail.com.

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 reasons: (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 different transfer programs. 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 household income and expenditure shares on energy for both residential utilities and commuting. The CEX also indicates that, for households within the same income group, the impact of energy price shocks on energy consumption for commuting can be opposite to their impact on energy consumption for residential utilities. Second, I develop a heterogeneous-agent incomplete market model building on Bewley-Imrohoroğlu-

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).

Huggett-Aiyagari, with an exogenous energy price, featuring non-homothetic consumption preferences, commuting costs, extensive and intensive margin labor supply choices, and a non-energy production sector that uses 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 my model, I find that an inflationary (a deflationary) energy price shock results in uneven welfare losses (gains) across households in different income groups, with low-income ones losing (gaining) the most. Fourth, I analyze the influence of work from home (WFH) and targeted transfer on the impact of an inflationary shock. I show that WFH mainly benefits high-income households due to their disproportionate access, exacerbating consumption inequality, while targeted transfer financed by higher earnings tax mitigates the shock's impact on consumption inequality.

In the model, households derive utility from a combination of energy and non-energy consumption. They also value leisure and decide whether to work, and if so, the number of hours. Those who choose to work consume additional energy for commuting, thereby incurring commuting costs, which depend on their earnings and appear as an expense in their budget constraints. Households earn labor and/or asset income, pay taxes, and receive transfers. They finance their consumption from disposable income and can borrow or save to insure against income fluctuations.

On the production side, perfectly competitive firms produce non-energy goods using labor, capital, and energy. To capture the low short-run elasticity of substitution between energy and non-energy factor inputs, firms combine these inputs in fixed proportions. Motivated by the literature and the fact that the energy price typically 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 firms' output is devoted to household non-energy consumption and exports to balance trade for energy imports.

An energy price shock directly impacts the composition of household energy and non-energy consumption. Due to the inelastic demand for energy 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 labor supply decisions. In addition, an energy price shock can indirectly impact 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 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 to calibrate parameters related to households' energy use in commuting. Commuting costs increase with 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, and expenditure shares on both residential and commuting energy.

I use the calibrated model to analyze the distributional effects of energy price shocks. An inflationary energy price shock increases household consumption costs, reducing real income and causing a rise in labor supply. This labor supply response 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, and reduced leisure increases disutility. The quantitative analysis finds that an energy price shock unevenly affects households across different income groups, with low-income households being impacted the most. A shock similar to the one in 2021 (equivalent to a 20% increase in the relative price of energy) results in welfare losses for the bottom income quintile almost twice as large as those for the top on impact (-1.25% vs. -0.75% in terms of consumption).

In the case of a 20% deflationary energy price shock, responses are opposite to those of an inflationary shock. However, its impacts on macroeconomic aggregates, such as capital, labor, real rate of return, wage, and output, are less pronounced than those of an inflationary shock. This aligns with empirical findings (e.g., Kilian, 2008). In terms of the distributional impact, the deflationary shock disproportionately increases low-income households' labor supply and consumption, reducing consumption inequality.

I also analyze the effects of an inflationary energy price shock in several alternative versions of my model to clarify the roles of its different features. First, a model with homothetic consumption preferences downplays the shock's impact on consumption inequality, as this model understates the energy share for low-income households and overstates it for high-income households. Second, without commuting costs, households can allocate their resources more flexibly, reducing consumption loss from an inflationary shock. Third, with only non-energy factors of production, energy price shocks do not directly impact the production sector. As a result, factor prices—rental rate and wage—are modestly affected, weakening the general equilibrium impact of a shock. For an inflationary shock, the weaker general equilibrium impact mitigates households' income and consumption loss, disproportionately benefiting high-income households.

Lastly, leveraging the baseline calibrated model, I conduct two policy experiments. First, motivated by the growing WFH opportunities, I examine how these opportunities influence the impact of an inflationary energy price shock. WFH significantly reduces commuting costs, allowing households to reallocate their resources to other consumption or investment. Nonetheless, access to WFH is typically more prevalent in high-skilled occupations, predominantly favoring high-skilled households (see, e.g., Bick, Blandin, and Mertens, 2023). I show that WFH mainly benefits households with such opportunity, while others continue to experience consumption losses similar to the no-WFH scenario, exacerbating consumption inequality. Second, motivated by the U.S. federal energy assistance program—the Low Income Home Energy Assistance Program (LIHEAP)—I examine the influence of targeted transfer on the impact of an inflationary energy price shock. I show that a lump-sum transfer to low-income households, financed by higher earnings tax, can mitigate the impact of an energy price shock on consumption inequality.

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. Related 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 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.[2] 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.[3] 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.

2. 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.

3. 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).

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 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 prices leads to a growing number of studies exploring its implications for different energy-related policies. In an open economy HANK model, Auclert, Monnery, Rognlie, and Straub (2023) show that monetary tightening is costly after an energy price shock but brings positive externalities for other energy importers. Conversely, fiscal policies, such as energy price subsidies and transfers, 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. Similar to these papers, I explore the impact of targeted transfer on responses to an inflationary energy price shock. Additionally, I explore the impact of WFH on these responses.

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

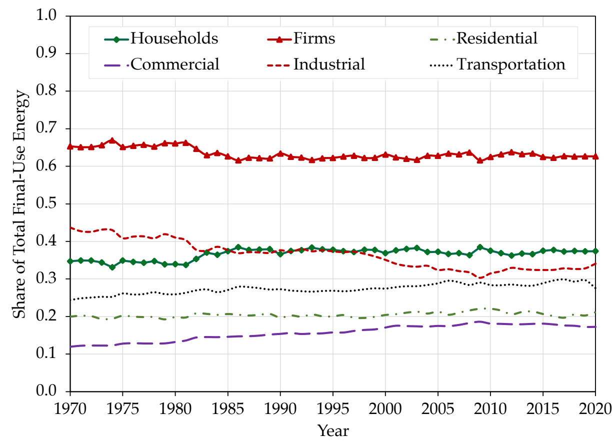


FIGURE 2
PATTERNS OF ENERGY CONSUMPTION

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).

sectors: residential, commercial, industrial, and transportation.[4] For my analysis, I reclassify these sectors into two categories: household and firm energy consumption. Household energy consumption includes residential utilities and transportation energy for personal vehicles. Firm energy consumption includes the remaining energy use in the transportation sector, as well as energy use 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).[5] Second, I calculate the price of energy in the transportation sector using consumption and expenditure data from the EIA. Finally, I obtain energy use for personal vehicles by dividing household expenditures on motor fuel by 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 all sectors have remained relatively constant, except for a slight decrease in the industrial sector and

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

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

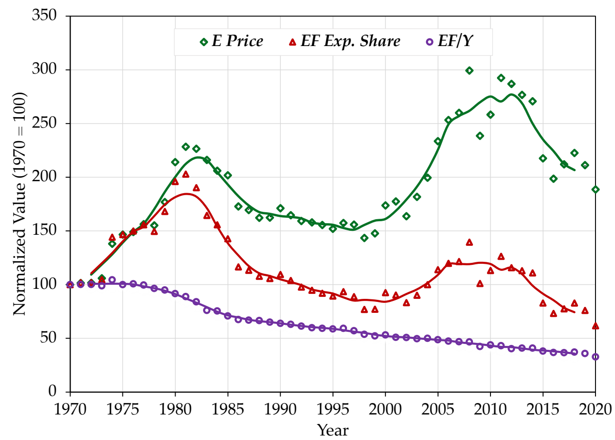


FIGURE 3
ENERGY INTENSITY OF OUTPUT

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.

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 to produce 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 the energy demand in the U.S. production sector since 1970. It plots firms' energy expenditure share (E_F exp. share), energy intensity of output (E_F/Y), and the average real price of final-use energy ($\tilde{p}_E$) from 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.[6] In contrast, the figure reveals a decline in energy intensity in the long run, which can result from technological change or sectoral reallocation (Sue Wing, 2008).[7]

3.3. *Heterogeneity in Energy Expenditure Shares Across Households*

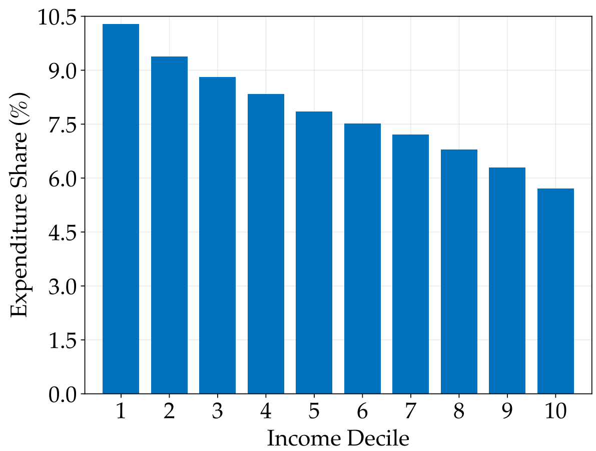
Data. I analyze variations in household energy consumption expenditures across income groups using quarterly household-level consumption expenditure data from the CEX. It is a nationally representative survey conducted by the Bureau of Labor Statistics (BLS) that reports data on income, expenditures,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

I use data spanning from 1999 to 2013, restricting the sample to households with heads aged 25 to 64, participated in at least four interviews, and are complete income reporters.[8] 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 for commuting to work; (ii) *residential energy*, which includes energy commodities used for purposes other than commuting to work; and (iii) *non-energy*.

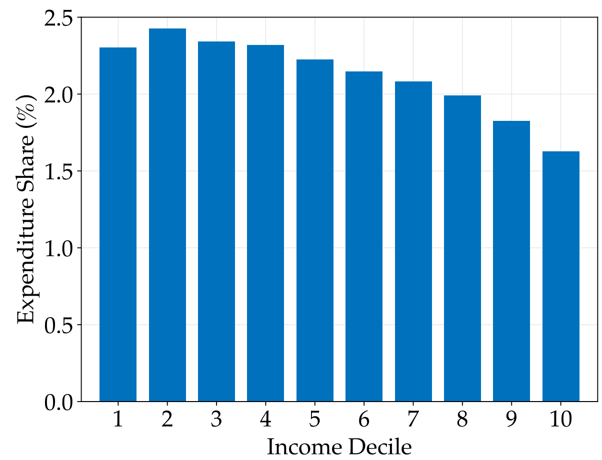
6. Hassler, Krusell, and Olovsson (2021) estimate the short-run elasticity of substitution between energy and non-energy inputs using maximum likelihood and find it close to zero.

7. 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).

8. I choose 2013 as the final year of my CEX sample due to the termination of the variable representing 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 the 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.

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 for commuting to work, I first 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 zero earners. The coefficient of the dummy variable represents the percentage change in gasoline expenditures between employed and non-employed households. I then use that coefficient to obtain employed households' energy expenditure for commuting to work. The remaining gasoline 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 (1999-2013). The figure reveals a clear negative correlation between household expenditure shares on energy and income levels. Specifically, the expenditure share on residential energy is 4.5

percentage points higher for the lowest income decile than the highest. For commuting energy, the difference between the lowest and highest income deciles 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.

3.4. Energy Price Shock and Consumption across Income Groups

As evidence of an energy price shock's distributional impact on consumption, I use the CEX interview survey to analyze how household consumption across different income groups changes following the 2021 energy price shock. The survey includes households in a maximum of four interviews over four consecutive quarters. For this analysis, I include households with heads aged 25 to 64 who participated in four interviews between 2021:Q1 and 2022:Q2.[9] The U.S. CPI indicates that the relative price of energy increased by almost 20% during this period. The reason for considering interviews in these six quarters instead of any consecutive four is to increase the sample size. I classify households into three income groups. To address potential sampling error, I limit the groups to three and use the CEX income rank (i.e., income percentiles) for classification.

In Table 1, I report descriptive statistics for households' first (Panel A) and fourth (Panel B) interviews. Columns 2 through 4 present statistics for three income groups, and the last column presents statistics for the full sample. The values in the table represent real consumption expenditures, which serve as a proxy for real consumption. I use twenty-two category-specific regional CPIs to deflate households' nominal consumption expenditures

9. The interview survey reports expenditures for the three months before the interview. Consequently, households interviewed in 2021:Q1 report their expenditures within 2020:Q4-2021:Q1, and those interviewed in 2022:Q2 report expenditures within 2022:Q1-2022:Q2.

TABLE 1
DESCRIPTIVE STATISTICS OF HOUSEHOLD EXPENDITURES IN THEIR FIRST AND FOURTH QUARTERS BETWEEN 2020:Q4 AND 2022:Q1

	Income Groups (Percentiles)		
	≤ 33	34-67	> 67
Panel A: First Quarter			
Quarterly Expenditure	$8188.54	$10917.89	$17715.40
	[$7269.71 $9107.37]	[$10185.21 $11650.57]	[$16466.13 $18964.67]
Energy	$766.39	$883.90	$1149.78
	[$690.73 $842.04]	[$833.88 $933.92]	[$1099.29 $1200.28]
Gasoline	$313.16	$403.64	$532.52
	[$261.99 $364.33]	[$370.59 $436.69]	[$496.83 $568.21]
Non-Gasoline	$453.23	$480.26	$617.26
	[$406.49 $499.96]	[$447.55 $512.97]	[$585.35 $649.17]
Commuting	$150.57	$195.81	$250.35
	[$126.36 $174.78]	[$179.66 $211.97]	[$233.05 $267.65]
Residential	$615.82	$688.09	$899.43
	[$556.96 $674.68]	[$649.00 $727.17]	[$860.52 $938.34]
Non-Energy	$7422.15	$10033.99	$16565.62
	[$6541.48 $8302.82]	[$9314.93 $10753.05]	[$15338.06 $17793.18]
Panel B: Fourth Quarter			
Quarterly Expenditure	$7233.69	$9434.09	$16031.61
	[$6404.71 $8062.66]	[$8925.21 $9942.96]	[$14727.52 $17335.71]
Energy	$718.69	$866.84	$1152.33
	[$645.27 $792.12]	[$819.13 $914.54]	[$1102.41 $1202.25]
Gasoline	$295.43	$425.90	$544.54
	[$242.14 $348.72]	[$392.97 $458.83]	[$513.78 $575.30]
Non-Gasoline	$423.26	$440.94	$607.78
	[$379.20 $467.33]	[$412.97 $468.90]	[$575.90 $639.67]
Commuting	$145.61	$204.77	$257.09
	[$119.14 $172.07]	[$188.73 $220.81]	[$242.29 $271.88]
Residential	$573.09	$662.07	$895.24
	[$518.65 $627.52]	[$626.03 $698.10]	[$855.84 $934.64]
Non-Energy	$6515.00	$8567.25	$14879.29
	[$5719.95 $7310.04]	[$8071.20 $9063.31]	[$13595.72 $16162.85]

Note. The table presents summary statistics of household quarterly consumption expenditures from the CEX interview survey. The sample is restricted to households with heads aged 25 to 64 who participated in four interviews between 2021:Q1 and 2022:Q2 and divided into three income groups. Panel A presents summary statistics from their first interview, while Panel B presents statistics from their fourth and final interview. Dollar amounts are deflated using category-specific regional CPIs, with 2020:Q4 as the base period. The 95% confidence intervals are in square brackets.

in respective categories, using 2020:Q4 as the base period.[10]

Comparing households' real expenditures in their first and fourth quarters, I find that

10. See Appendix B.2 for details.

overall expenditure decreases across all income groups, with the middle income group experiencing the largest reduction (-13.59%), followed by the bottom (-11.66%) and the top (-9.50%). Specifically, energy expenditure decreases by 6.22% for the bottom income group and by 1.93% for the middle, while the top income group's energy expenditure remains almost unchanged. Within the energy category, gasoline expenditure increases by 5.51% for the middle income group and 2.25% for the top but decreases by 5.66% for the bottom. Conversely, non-gasoline energy expenditures decrease for all groups, with 6.61% for the bottom, 8.18% for the middle, and 1.54% for the top.

Following my energy classification, commuting energy expenditure increases by 4.58% for the middle and 2.69% for the top group, while falling by 3.29% for the bottom. On the other hand, residential energy expenditure declines for all groups, with the bottom group experiencing the largest reduction (-6.94%) and the top group the smallest (-0.5%). Finally, non-energy consumption expenditures substantially decline for all groups, with 14.62% for the middle, followed by 12.22% for the bottom, and 10.18% for the top.

Overall, the results indicate that commuting and residential energy consumption do not necessarily respond in the same way to an energy price shock, and the impact of such shocks can differ across households in different income groups.

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.[11]

4.1. Technology

Firms in a perfectly competitive sector operate using capital, labor, and energy as 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; Casey, 2023), 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 κA_{Et} represents the energy efficiency of the production technology.[12] A_{Et} captures energy-efficient technological progress and $\kappa > 0$ is the base energy efficiency level in the absence of technological progress.[13] 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 δ 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

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

12. 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).

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

fraction is exported to balance trade for the economy's energy imports.

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 $\beta \in (0,1)$ be the time discount factor, then the household's lifetime utility is given by

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

where $\mathbb{E}_0$ denotes the expectation 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 taxes on its pre-government income 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 τ^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, $\boldsymbol{x}_t$.

In contrast, 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

Each period, a representative firm 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 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 in production, implying that a change in the energy price or energy efficiency can directly impact both 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 Γ_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:

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

(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:

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

(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. 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.[14]

5.1. Technology

Following the literature, I set the output elasticity of capital α to 0.36. 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 κ 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 δ is set to 1.53% per quarter, equivalent to a yearly depreciation rate of 6%.

14. For readers' convenience, I present the externally assigned and estimated parameter values in Table F.1 and provide an overview of the internal calibration strategy and calibrated parameters in Table F.2.

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 ρ_z to 0.975 and the standard deviation σ_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, π_{up} and π_{stay}, where π_{up} represents the probabilities of transitioning from z to $z_{\max}$ and π_{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 (66.44%); (ii) the earnings share of the top earnings decile (35.04%); and (iii) the earnings share of the top 1% of the earnings distribution (11.62%).[15] This procedure yields $z_{\max} = 20.85$, $\pi_{\text{up}} = 7.03 \times 10^{-4}$, and $\pi_{\text{stay}} = 0.98$.

5.3. *Preferences*

I set the time discount factor β 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 β of 0.981.

I specify the household's period utility function as

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

15. All three data moments are computed using the biennial waves of the Panel Study of Income Dynamics (PSID) from 1999 to 2013, focusing on households with heads aged 25 to 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 γ to 2, a commonly used value in the literature. The household level Frisch elasticity of labor supply ν 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 φ_1 is set to 38.84, ensuring that in the steady state, on average, employed households work one-third of their time endowment. I set the fixed utility cost from working φ_2 to 0.52, such that the model reproduces the aggregate employment rate of 79.63% 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. ϵ_{E_R} and ϵ_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 which rationalizes the systemic variation in different types of goods demanded at different income levels.[16] 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 (ω_{E_R}) and non-energy (ω_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 2.[17]

I set the remaining preference parameter Ω_{E_R} to match the average household expenditure share on residential energy in the steady state to its empirical counterpart of 7.94% from the CEX. This procedure yields a value for Ω_{E_R} of 0.08.

16. See Matsuyama (2019) and Comin, Lashkari, and Mestieri (2021) for details.

17. In Appendix C, I show the expenditure elasticities computed using the structurally estimated parameter values are consistent with their respective reduced-form estimates.

TABLE 2
DEMAND ESTIMATION

Parameter	(1)	(2)	(3)
σ	0.251***	0.303***	0.248***
	(0.015)	(0.014)	(0.021)
ϵ_{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 (≤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 τ^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.[18] Following Heathcote, Storesletten, and Violante (2020), I set

18. 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 τ^l

τ^l to 0.09, an estimate obtained by excluding transfers from disposable income. Given τ^l and government expenditures, λ balances the government budget. This procedure yields a value for λ of 0.79. λ 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 finance, first proposed by Feldstein (1969) and more recently used by Bénabou (2000, 2002), and Heathcote, Storesletten, and Violante (2017), henceforth also known as the HSV tax function. 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. First, the tax function implies that marginal taxes are 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. Second, 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. 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 0.24, ensuring that in the steady state, the average transfers-to-earnings ratio of the lowest wealth quintile is 14.72%.

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

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.

Survey (ATUS) (see Kimbrough, 2019).[19]

I set ι_0 to 0.02, ensuring that, in the steady state, employed households' average expenditure share on commuting energy matches its empirical counterpart (2.0%). The sensitivity parameter ι_1 is set to 0.58 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).

5.6. Borrowing Limit

The exogenous borrowing limit $\underline{a}$ is set to ensure that the steady-state share of households with negative assets matches its empirical counterpart (12.58%). This procedure yields a value of $\underline{a}$ equal to -0.07, which is equivalent to -6.0% 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 3 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.

Panel A of Figure 5 compares the employment rates by income quintiles in the model and the data, while Panel B 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

19. 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 G.4—the expenditure on commuting energy increases with the number of earners in the household.

TABLE 3
TARGETED MOMENTS: BASELINE

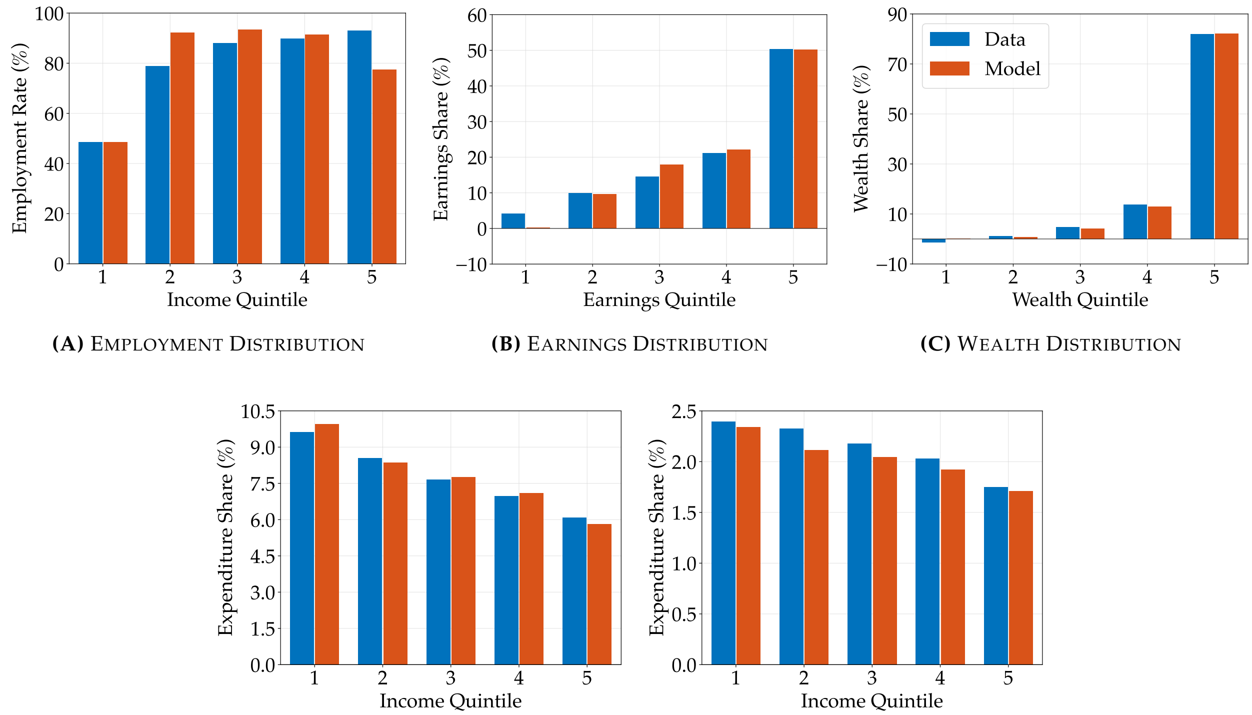
Moment	Data	Model
Firms' expenditure on energy as a share of GDP	4.10%	4.10%
Wealth share of top wealth decile	66.44%	64.88%
Earnings share of top earnings decile	35.04%	35.12%
Earnings share of top 1% of the earnings distribution	11.62%	14.32%
After-tax rate of return	4.10%	4.11%
Average expenditure share of E_R in consumption basket	7.94%	7.93%
Employed households' average share of hours worked	33.33%	33.34%
Employment rate	79.63%	80.64%
Government purchases as a share of GDP	20.0%	20.0%
Average transfers-to-earnings ratio of the lowest wealth quintile	14.72%	15.97%
Employed households' average expenditure share on E_T	2.00%	2.00%
Bottom-to-top income quintile workers' expenditure share on E_T	1.37	1.37
Share of households with negative wealth	12.58%	10.49%

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.

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. Panel D of Figure 5 compares the expenditure shares on residential energy by income quintiles in the model and the data, while Panel E compares those on commuting energy. The figure shows that the model effectively reproduces observed expenditure shares across income quintiles for both types of energy consumption.

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.



(A) EMPLOYMENT DISTRIBUTION

(B) EARNINGS DISTRIBUTION

(C) WEALTH DISTRIBUTION

(D) RESIDENTIAL ENERGY EXPENDITURE SHARE DISTRIBUTION

(E) COMMUTING ENERGY EXPENDITURE SHARE DISTRIBUTION

FIGURE 5

CROSS-SECTIONAL DISTRIBUTIONS – DATA VS. MODEL

Note. The figure shows cross-sectional moments from the model and the data. Panel A shows the distribution of employment rates by income quintiles. Panel B shows earnings shares by earnings quintiles. Panel C shows wealth shares by wealth quintiles. Panel D shows expenditure shares on residential energy by income quintiles. Panel E shows expenditure shares on commuting energy by income quintiles. The empirical moments of employment and earnings distributions are computed using the biennial waves of the PSID from 2001 to 2015, while the moments of the wealth distribution are computed using the PSID waves from 1999 to 2013. This is because the PSID waves record labor market variables from the previous year. The expenditure shares for residential and commuting energy are calculated using the quarterly waves of the CEX from 1999 to 2013 on households that participated in at least four interviews and are complete income reporters. In all cases, the sample is restricted to households with heads aged 25 to 64.

7. QUANTITATIVE ANALYSIS

In this section, I conduct a set of quantitative experiments to examine the effects of energy price shocks. First, using the baseline calibrated model, I explore the effects of both inflationary and deflationary energy price shocks in separate exercises. Next, I analyze how the responses to an inflationary energy price shock change in different versions of my

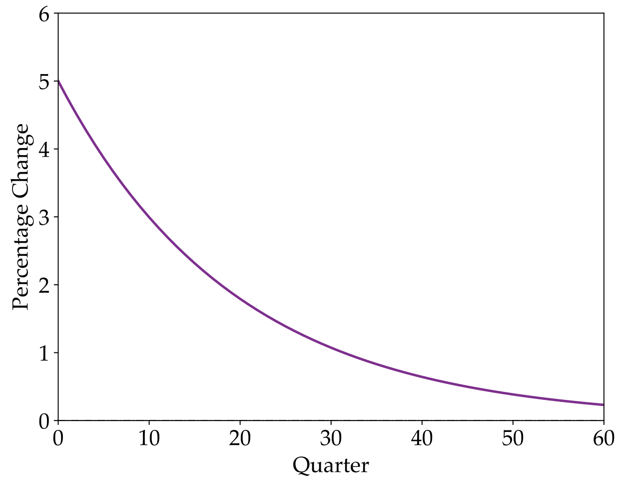


FIGURE 6
IMPULSE RESPONSE OF ENERGY PRICE TO A ONE STANDARD DEVIATION SHOCK TO ITSELF

model.[20] These exercises help to understand the roles of different features of the model. Finally, I examine the impacts of WFH opportunity and targeted transfer on the responses to an inflationary energy price shock.

7.1. Energy Price Shock

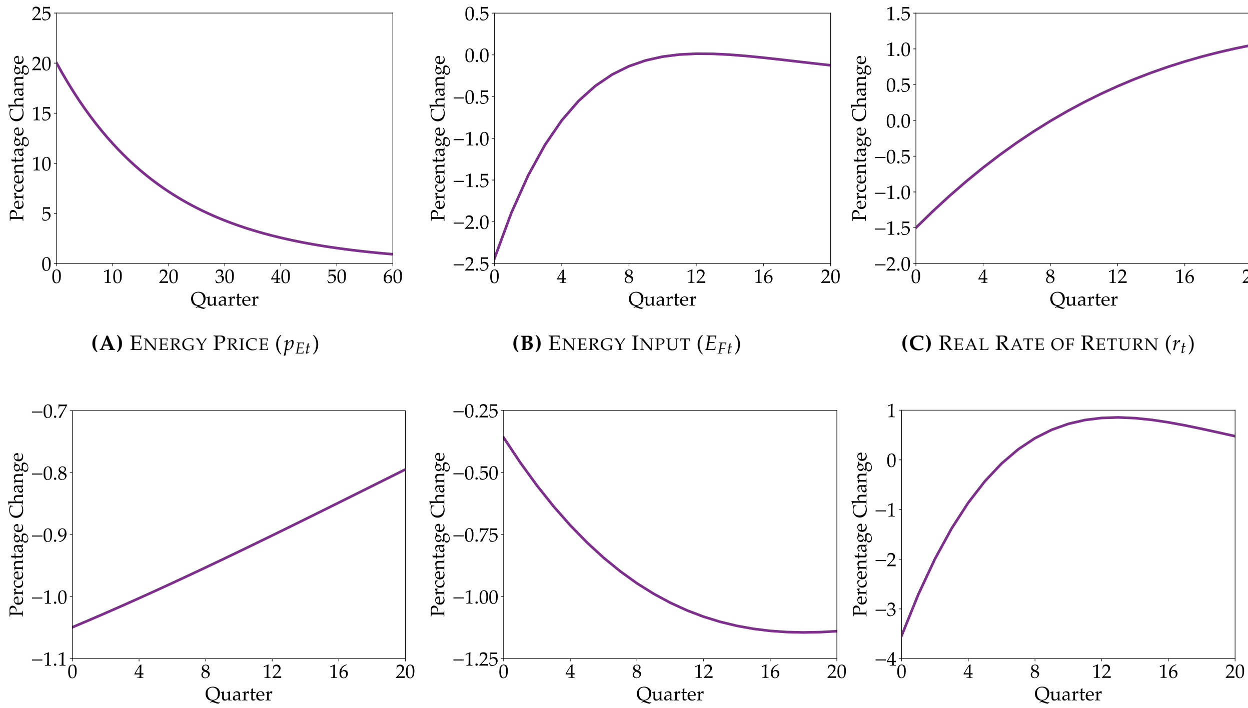
I assume that a shock to the energy price is AR(1).[21] Therefore, p_{Et} is determined by

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

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 6.

I choose the persistence of the shock $\rho_{p_E} = 0.96$, which is equivalent to a shock with a half-life of approximately four years (i.e., the time it takes for the shock's effect to halve in

20. Appendix F.2 describes the calibrations of alternative models.
21. It is important to mention that using an augmented Dickey-Fuller test, at a 5% level of significance, I cannot reject the null hypothesis of a unit root in the energy price process. However, it is challenging to derive impulse responses to a non-stationary shock. Therefore, the literature often treats shocks to energy price 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) ENERGY PRICE (p_{Et}) **(B)** ENERGY INPUT (E_{Ft}) **(C)** REAL RATE OF RETURN (r_t)

(D) WAGE (w_t) **(E)** CAPITAL (K_{t+1}) **(F)** LABOR (L_t)

FIGURE 7
RESPONSES OF MACROECONOMIC AGGREGATES TO A TWENTY PERCENT INFLATIONARY ENERGY PRICE SHOCK IN THE BASELINE MODEL

magnitude), and a volatility of $\sigma_{p_E} = 0.05$.[22]

7.2. *Effects of an Inflationary Energy Price Shock*

I now use the baseline calibrated model to examine the impact of an inflationary energy price shock similar to the one in 2021 (equivalent to a 20% increase in p_E). As shown in Figure 7, the rise in energy price increases firms' production costs, leading them to reduce energy use in production. Consequently, the marginal productivities of non-energy factors decline, reducing wage and rental rates.

The high energy price increases household consumption expenditures, reducing their real income and compelling them to adjust their labor supply and savings decisions.[23] Panel B of Figure 8 shows that labor supply responses vary across households. Due to

22. See Table G.2 for details.
23. The continuous decline in aggregate capital over a long period can result from investment falling below depreciation. The high energy price decreases household income and increases expenditures, reducing investment.

higher marginal utility, low-income households are more inclined to increase their labor supply. Additionally, they lack savings to insure against the real income loss induced by the higher energy price, leading them to rely on increasing their labor supply to smooth consumption. However, this increase in labor supply results in additional welfare losses, as higher commuting costs constrain other consumption, and reduced leisure diminishes overall utility. On the other hand, for high-income households, diminishing returns from work make leisure preferable to work, decreasing energy use for commuting.[24]

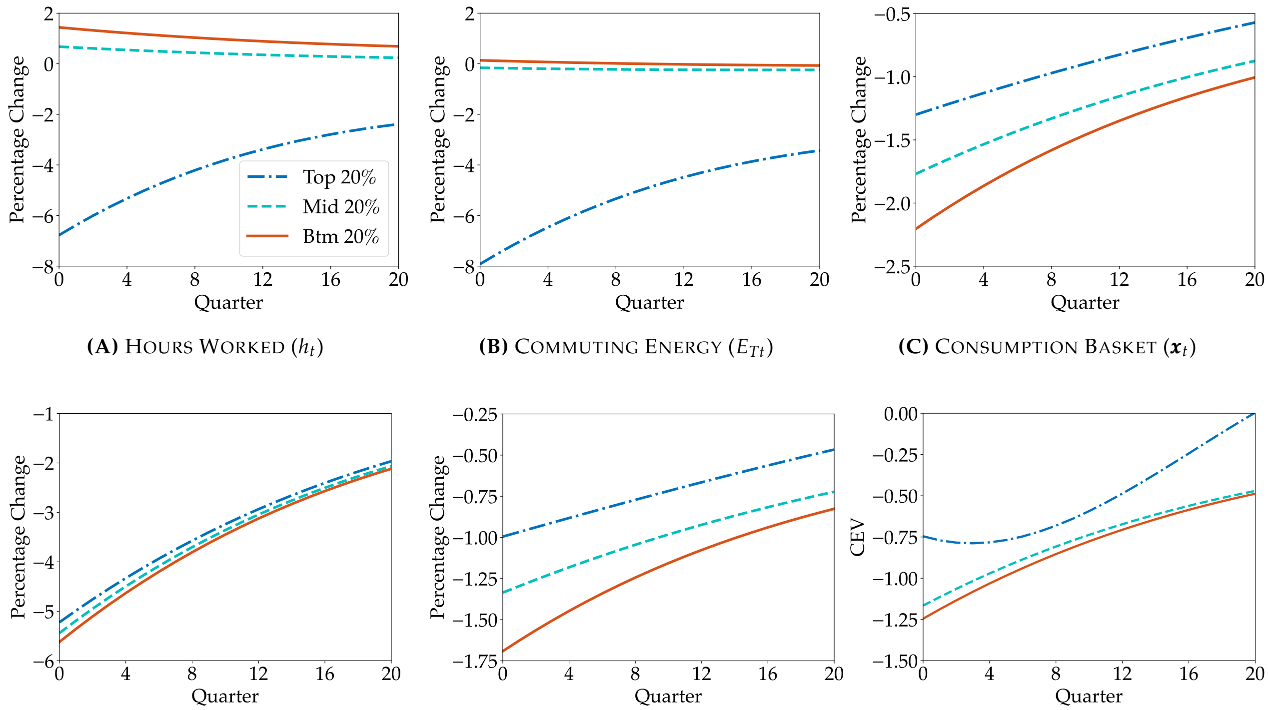
Panel C of Figure 8 shows that the size of the consumption basket decreases for households in the lowest income quintile by almost twice as much as for those in the top quintile. This decline is due to reductions in both residential energy and non-energy consumption. Panel D shows that residential energy consumption decreases by approximately the same percentage across all income groups. However, Panel E indicates that the adjustment in non-energy consumption varies across income groups. Panel F shows that the shock results in welfare losses for the bottom income quintile almost twice as large as those for the top quintile on impact (-1.25% vs. -0.75% in terms of consumption).[25]

7.3. *Effects of a Deflationary Energy Price Shock*

In addition to the inflationary energy price shock, I explore the effects of a deflationary energy price shock to directly compare the outcomes. For consistency, I assume that the deflationary shock decreases the energy price by 20% on impact. The outcomes from this exercise are presented in Figure 9. As shown in the figure, compared to the responses to an

24. Following an inflationary energy price shock, high-income households decrease their labor supply due to the declining wage rate and increasing commuting costs. In Figure G.8, I show that in a full-employment model, shutting down the trade-off between earnings and commuting costs by fixing commuting energy to the pre-shock steady-state level increases labor supply even for the top-income quintile in response to an inflationary energy price shock. In terms of energy use for commuting, the model outcome contrasts with the empirical findings from the CEX in Table 1. This discrepancy could arise for two main reasons. First, in the real world, low-income households can switch to public transportation in response to an inflationary energy price shock, decreasing their energy use for commuting. However, my model features no alternatives for commuting, making low-income households' energy use more inelastic. Second, households' commuting distances usually remain mostly unchanged, resulting in minimal changes in high-income households' energy use for commuting following an energy price shock. When the model shuts down the trade-off between earnings and commuting costs (as in Figure G.8), it prevents the large decline in high-income households' commuting energy use.

25. Welfare is measured in terms of the consumption equivalent variation (CEV).



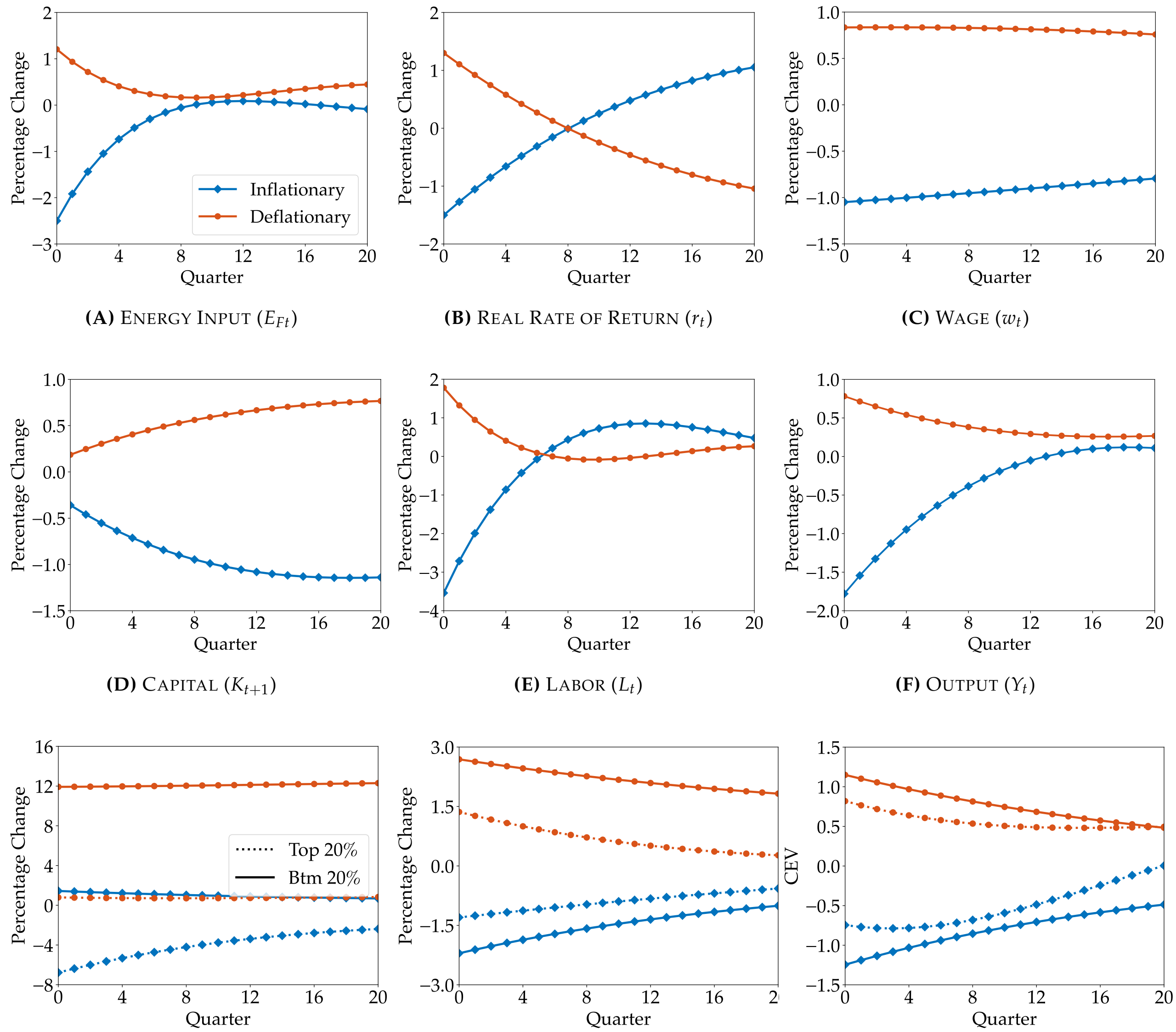
(A) HOURS WORKED (h_t) **(B)** COMMUTING ENERGY (E_{Tt}) **(C)** CONSUMPTION BASKET ($\boldsymbol{x}_t$)

(D) RESIDENTIAL ENERGY (E_{Rt}) **(E)** NON-ENERGY (C_t) **(F)** WELFARE

FIGURE 8
DISTRIBUTIONAL RESPONSES TO A TWENTY PERCENT INFLATIONARY ENERGY PRICE SHOCK IN THE BASELINE MODEL

inflationary energy price shock, the deflationary shock has the opposite impact on macroeconomic aggregates, such as energy and non-energy factors of production, rate of return, wage, and output. However, the effects are less pronounced than those of the inflationary shock, which aligns with empirical findings (see, e.g., Kilian, 2008).

In terms of the distributional effect, similar to the inflationary energy price shock, households in the bottom income quintile are impacted the most. However, in this case, their labor supply and consumption responses are larger than those to the inflationary shock. For households in the top income quintile, the labor supply response to the deflationary energy price shock is almost muted, while their consumption response is opposite but similar in magnitude to their response to the inflationary shock.



(A) ENERGY INPUT (E_{Ft}) **(B)** REAL RATE OF RETURN (r_t) **(C)** WAGE (w_t)

(D) CAPITAL (K_{t+1}) **(E)** LABOR (L_t) **(F)** OUTPUT (Y_t)

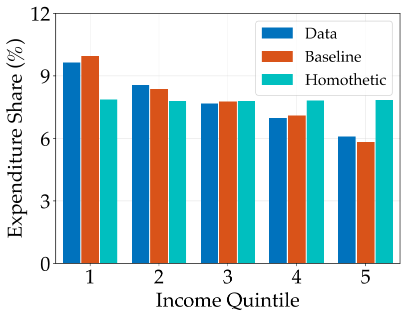
(G) HOURS WORKED (h_t) **(H)** CONSUMPTION BASKET ($\boldsymbol{x}_t$) **(I)** WELFARE

FIGURE 9

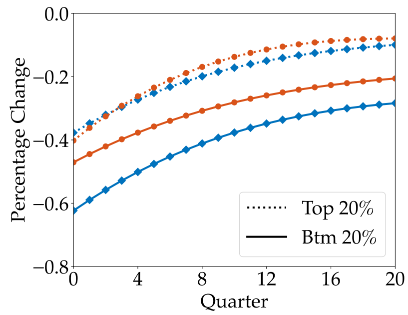
RESPONSES TO A TWENTY PERCENT DEFLATIONARY ENERGY PRICE SHOCK IN THE BASELINE MODEL

7.4. *Comparison with Models Under Alternative Assumptions*

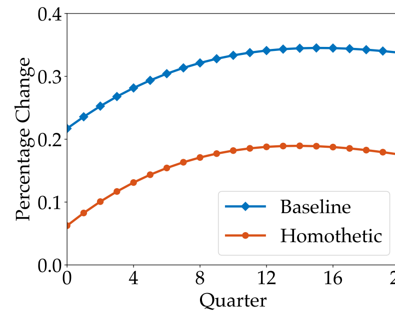
Homothetic Consumption Preferences. While the Engel curve of energy consumption suggests non-homothetic consumption preferences, this is often simplified in the literature by assuming homotheticity (e.g., Auclert, Bardóczy, Rognlie, and Straub, 2021). To explore the importance of non-homothetic consumption preferences, I now compare the consumption responses in the baseline model with those from a model calibrated with homothetic



(A) E_R EXPENDITURE SHARE



(B) CONSUMPTION BASKET (x_t)



(C) CONSUMPTION GINI

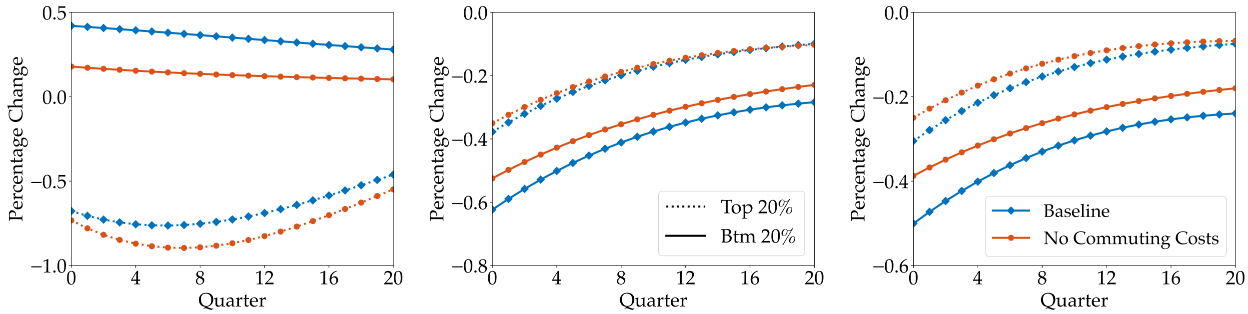
FIGURE 10
CONSUMPTION RESPONSES TO A ONE STANDARD DEVIATION INFLATIONARY ENERGY PRICE SHOCK IN A MODEL WITH HOMOTHETIC CONSUMPTION PREFERENCES

consumption preferences (henceforth, the homothetic model).

As shown in Figure 10, an inflationary energy price shock impacts the consumption basket of the bottom income quintile less in the homothetic model than in the baseline model. The homothetic model understates the residential energy share of low-income households, lowering their burden from the high energy price and thus reducing their consumption drop. Although this model overstates the residential energy share of high-income households, their consumption response is similar to that in the baseline model. This is because the increase in their expenditures from the additional energy share in their consumption baskets is minimal compared to their total expenditures. Consequently, the impact of an inflationary energy price shock increases consumption inequality moderately in the homothetic model compared to the baseline model.

No (Explicit) Commuting Costs. One of the unique features of my model is its explicit inclusion of commuting costs. This feature makes the model suitable for evaluating a wider range of policies compared to models without it. Conventional models in the literature typically combine households' energy use for commuting with their other energy consumption in the consumption basket. As a result, in response to an energy price shock, households adjust their composition of energy and non-energy consumption without differentiating between residential and commuting energy.

Figure 11 shows that in a model without explicit commuting costs, an inflationary en-



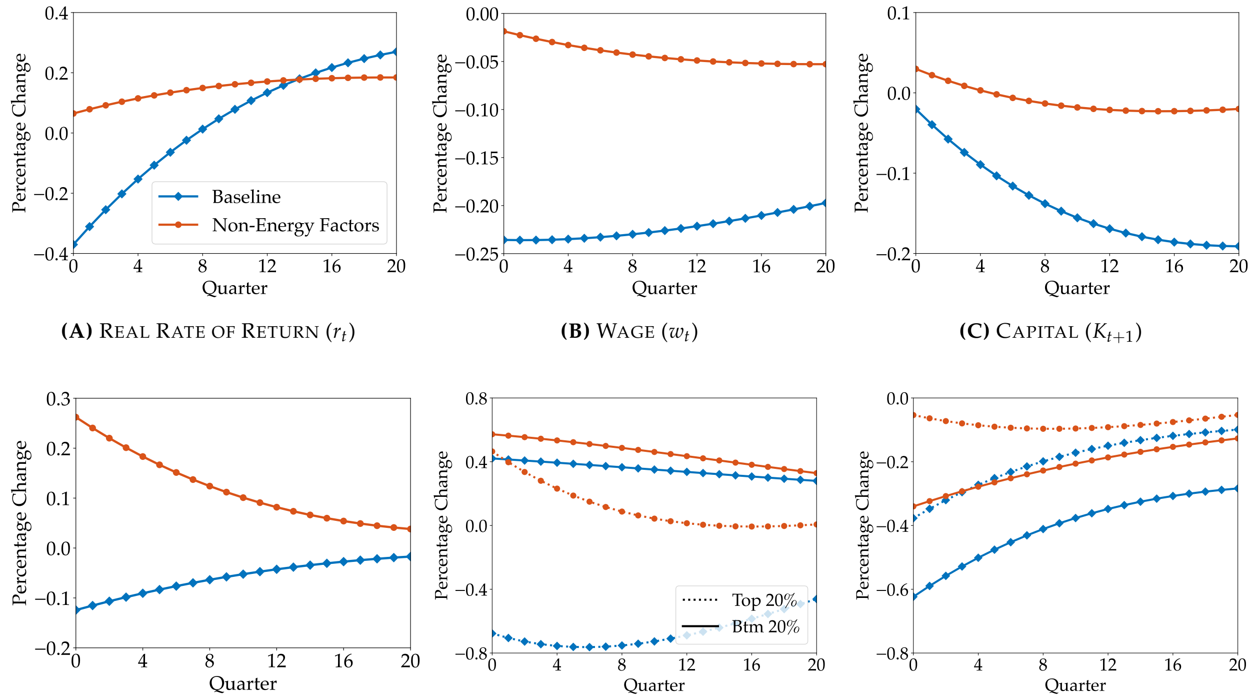
(A) Hours Worked (h_t) **(B)** Consumption Basket (x_t) **(C)** Non-Energy Consumption

Figure 11
Consumption and Labor Supply Responses to a One Standard Deviation Inflationary Energy Price Shock in a Model without Explicit Commuting Costs

ergy price shock results in a moderate loss in the consumption basket on impact compared to the baseline model. Specifically, the consumption loss of households in the lowest income quintile is disproportionately less than in the baseline model. This is because explicit commuting costs in the baseline model make the demand for commuting energy more inelastic relative to households' other (residential) energy demand, causing additional expenses and reducing resources available for their consumption baskets.[26] The higher drop in the consumption basket increases marginal utility, prompting households in the baseline model to work more. However, as households in the lowest income quintile typically have low labor market productivity, working more hours is insufficient to compensate for the losses incurred from explicit commuting costs.

No Energy as a Factor of Production. While the primary focus of my paper is the distributional impact of energy price shocks, my baseline model includes energy as a factor of production in addition to its use for commuting and residential utilities. Since, in the U.S., a large share of total energy is used in the production sector, including it as a factor of production is crucial to capture the general equilibrium (indirect) effect of a shock. Nonetheless, I now explore how the responses to an inflationary shock in my model would differ if the endogenous production sector only used non-energy factors.

26. Using U.S. data, empirical literature shows that the demand for commuting energy, such as gasoline, is more inelastic than electricity, the primary non-gasoline energy category (see, e.g., Alberini, Gans, and Velez-Lopez, 2011).



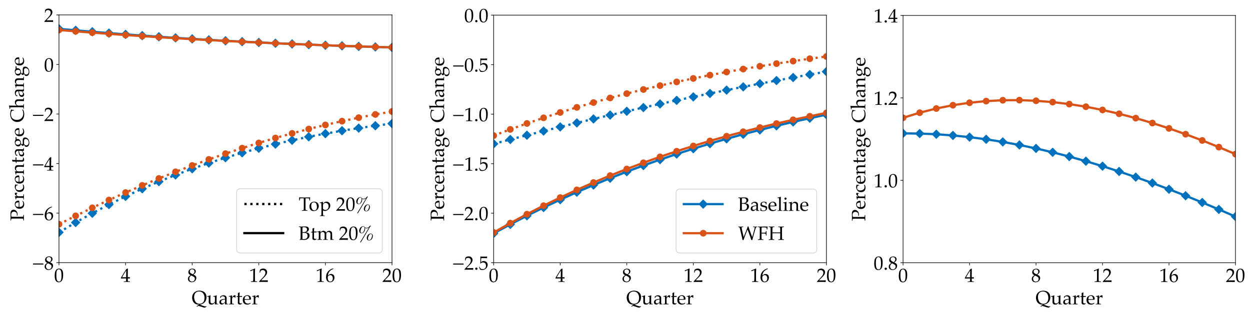
(A) Real Rate of Return (r_t) **(B)** Wage (w_t) **(C)** Capital (K_{t+1})

(D) Labor (L_t) **(E)** Hours Worked (h_t) **(F)** Consumption Basket ($\boldsymbol{x}_t$)

Figure 12

Responses to a One Standard Deviation Inflationary Energy Price Shock in a Model with Non-Energy Factors of Production

Since energy is taken as an imported good at an exogenous price, an inflationary energy price shock can impact the demand for the output of the endogenous production sector in two ways. First, additional output is required for each unit of energy imported to balance the economy's resource constraint. Second, households' energy and non-energy consumption can decline due to the loss in their real income from the high energy price. With only non-energy factors of production, energy price shocks do not directly impact the production sector. As a result, as shown in Figure 12, factor prices—rental rate and wage—are modestly affected, weakening the indirect impact of a shock. For an inflationary energy price shock, while the weaker indirect impact mitigates income loss and, ultimately, consumption loss for all households, it disproportionately benefits high-income households due to their higher asset holdings and labor productivity.



(A) Hours Worked (h_t) **(B)** Consumption Basket (x_t) **(C)** Consumption Gini

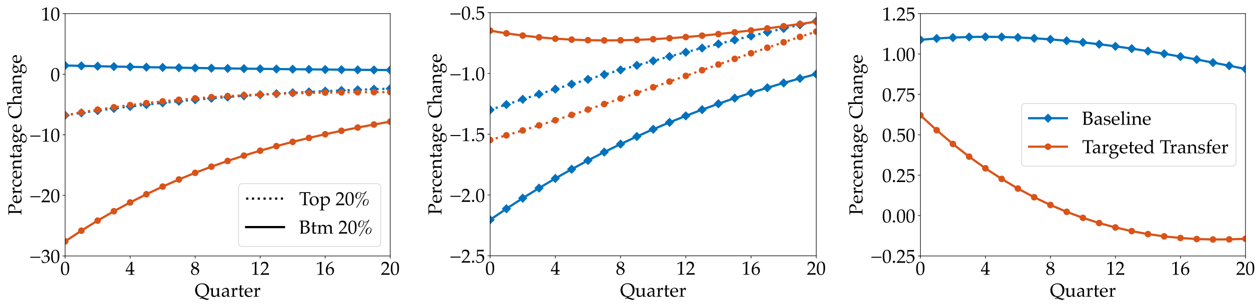
Figure 13
Consumption and Labor Supply Responses to Work from Home Opportunity Following an Inflationary Energy Price Shock

7.5. *Policy Analysis*

Work from Home Opportunity. Given the growing trend of WFH opportunities, especially since the COVID-19 pandemic, it is crucial to understand its impact on the effects of energy price shocks. WFH significantly reduces commuting costs, allowing households to reallocate these resources to their consumption or investment. However, WFH opportunities are 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 WFH opportunities influences the distributional effects of energy price shocks.

To explore the implications of WFH, I assume that following an inflationary energy price shock, partial WFH becomes permanently feasible for households in the top quintile of the earnings distribution in the pre-shock steady state. This reduces their commuting energy consumption to half of what it would be without the WFH opportunity for the same level of earnings. As a result, their commuting costs decrease, leaving more resources for non-energy and residential energy consumption. Figure 13 shows that the loss in the consumption basket for households in the top earnings quintile is less with the WFH opportunity. However, the loss in the consumption basket for the bottom earnings quintile remains similar to the no WFH scenario, increasing consumption inequality.

Targeted Transfer Program. In the U.S., a federally funded program known as the Low



(A) HOURS WORKED (h_t) **(B)** CONSUMPTION BASKET ($\boldsymbol{x}_t$) **(C)** CONSUMPTION GINI

FIGURE 14
CONSUMPTION AND LABOR SUPPLY RESPONSES TO A TARGETED TRANSFER PROGRAM FOLLOWING AN INFLATIONARY ENERGY PRICE SHOCK

Income Home Energy Assistance Program (LIHEAP) provides financial assistance to low-income households for their energy expenditures. The program mainly helps with home energy expenses such as heating and cooling. However, a few states have adapted LIHEAP to cover gas and electric bills as well.[27] Motivated by this energy assistance program, I now explore how a lump-sum transfer to low-income households influences the impacts of an inflationary energy price shock in my model.

To implement the targeted transfer program following an inflationary energy price shock, I provide a lump-sum transfer equivalent to 3% of the per-capita pre-tax income to households in the lowest income quintile in the pre-shock steady state in my model.[28] While implementing the transfer, I ensure that a temporary shock does not result in a permanent transfer. Thus, the transfer amount declines with the energy price over time, maintaining the same persistence. The government finances the transfer from tax revenues and maintains a balanced budget period by period by adjusting λ in the HSV tax function. As shown in Figure 14, while this transfer significantly reduces the consumption loss of the targeted group, the top income quintile faces greater consumption loss due to their heavier

27. For example, 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). To be eligible for CEAP, households must have an income at or below 150% of the Federal Poverty Guidelines. Additionally, households that participate in or have family members who receive SNAP, TANF, Supplemental Security Income (SSI), or certain Means Tested Veterans Program payments automatically meet the eligibility requirements.
28. I choose the transfer amount based on the current energy assistance program in the U.S. In 2020, the program provides up to $2,000 annually in Texas, which is approximately 3% of an annual per-capita pre-tax income of $60,000.

tax burden. Consequently, in response to an inflationary energy price shock, consumption inequality increases less than in the no-transfer scenario.

8. Concluding Remarks

This paper studies the distributional effects of energy price shocks 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 sector that uses energy and non-energy factors 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 distributions of residential and commuting energy expenditure shares. An energy price shock in my model unevenly impacts households across different income groups, with low-income households being affected the most.

The paper also explores how WFH opportunity and targeted transfer influence the impact of an inflationary energy price shock. It shows that WFH mainly benefits high-income households due to their disproportionate access, exacerbating consumption inequality. On the other hand, a lump-sum transfer to low-income households, financed by higher earnings tax, mitigates the shock's impact on consumption inequality.

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 at an exogenous price, incorporating an endogenous energy production sector alongside energy imports could make the model more realistic for the U.S. economy. Second, considering multiple non-energy sectors based on their energy intensity could be a meaningful extension. Energy price shocks may disproportionately affect sectors heavily relying on energy, impacting all associated entities. Conversely, sectors with low energy dependency might experience more muted effects. Finally, by distinguishing between energy-efficient and energy-intensive durables, one can explore how energy price shocks impact the adoption of energy-efficient durables across different income and wealth groups.

References

Aguiar, Mark and Mark Bils (2015). Has Consumption Inequality Mirrored Income Inequality? *American Economic Review*, 105(9), 2725–56.

Aiyagari, S. Rao (1994). Uninsured Idiosyncratic Risk and Aggregate Saving. *The Quarterly Journal of Economics*, 109(3), 659–684.

Alberini, Anna, Will Gans, and Daniel Velez-Lopez (2011). Residential consumption of gas and electricity in the U.S.: The role of prices and income. *Energy Economics*, 33(5), 870–881.

Alpanda, Sami and Adrian Peralta-Alva (2010). Oil Crisis, Energy-Saving Technological Change and the Stock Market Crash of 1973–74. *Review of Economic Dynamics*, 13(4), 824–842.

Auclert, Adrien, Bence Bardóczy, Matthew Rognlie, and Ludwig Straub (2021). Using the Sequence-Space Jacobian to Solve and Estimate Heterogeneous-Agent Models. *Econometrica*, 89(5), 2375–2408.

Auclert, Adrien, Hugo Monnery, Matthew Rognlie, and Ludwig Straub (2023). Managing an Energy Shock: Fiscal and Monetary Policy. Working Paper 31543, National Bureau of Economic Research.

Auclert, Adrien, Matthew Rognlie, Martin Souchier, and Ludwig Straub (2021). Exchange Rates and Monetary Policy with Heterogeneous Agents: Sizing up the Real Income Channel. Working Paper 28872, National Bureau of Economic Research.

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis (2023). The Evolution of Work from Home. Working Paper 31686, National Bureau of Economic Research.

Barsky, Robert B. and Lutz Kilian (2004). Oil and the Macroeconomy Since the 1970s. *Journal of Economic Perspectives*, 18(4), 115–134.

Baumeister, Christiane and Lutz Kilian (2014). Do Oil Price Increases Cause Higher Food Prices? *Economic Policy*, 29(80), 691–747.

Baumeister, Christiane and Lutz Kilian (2016). Forty Years of Oil Price Fluctuations: Why the Price of Oil May Still Surprise Us. *Journal of Economic Perspectives*, 30(1), 139–60.

Bewley, Truman (1983). A Difficulty with the Optimum Quantity of Money. *Econometrica*, 51(5), 1485–1504.

Bick, Alexander, Adam Blandin, and Karel Mertens (2023). Work from Home before and after the COVID-19 Outbreak. *American Economic Journal: Macroeconomics*, 15(4), 1–39.

Boppart, Timo, Per Krusell, and Kurt Mitman (2018). Exploiting MIT Shocks in Heterogeneous-Agent Economies: the Impulse Response as a Numerical Derivative. *Journal of Economic Dynamics and Control*, 89, 68–92. Fed St. Louis-JEDC-SCG-SNB-UniBern Conference, titled: "Fiscal and Monetary Policies".

Bénabou, Roland (2000). Unequal Societies: Income Distribution and the Social Contract. *American Economic Review*, 90(1), 96–129.

Bénabou, Roland (2002). Tax and Education Policy in a Heterogeneous-Agent Economy: What Levels of Redistribution Maximize Growth and Efficiency? *Econometrica*, 70(2), 481–517.

Casey, Gregory (2023). Energy Efficiency and Directed Technical Change: Implications for Climate Change Mitigation. *The Review of Economic Studies*, 91(1), 192–228.

Castañeda, Ana, Javier Díaz-Giménez, and José-Víctor Ríos-Rull (2003). Accounting for the U.S. Earnings and Wealth Inequality. *Journal of Political Economy*, 111(4), 818–857.

Comin, Diego, Danial Lashkari, and Martí Mestieri (2021). Structural Change With Long-Run Income and Price Effects. *Econometrica*, 89(1), 311–374.

de Ferra, Sergio, Kurt Mitman, and Federica Romei (2020). Household Heterogeneity and the Transmission of Foreign Shocks. *Journal of International Economics*, 124, 103303. NBER International Seminar on Macroeconomics 2019.

Del Canto, Felipe N, John R Grigsby, Eric Qian, and Conor Walsh (2023). Are Inflationary Shocks Regressive? A Feasible Set Approach. Working Paper 31124, National Bureau of Economic Research.

Dhawan, Rajeev and Karsten Jeske (2008). Energy Price Shocks and the Macroeconomy: The Role of Consumer Durables. *Journal of Money, Credit and Banking*, 40(7), 1357–1377.

Dhawan, Rajeev, Karsten Jeske, and Pedro Silos (2010). Productivity, energy prices and the great moderation: A new link. *Review of Economic Dynamics*, 13(3), 715–724.

Diaz-Gimenez, Javier, Andrew Glover, and José-Víctor Ríos-Rull (2011). Facts on the Distributions of Earnings, Income, and Wealth in the United States: 2007 Update. *Quarterly Review*.

Edelstein, Paul and Lutz Kilian (2009). How sensitive are consumer expenditures to retail energy prices? *Journal of Monetary Economics*, 56(6), 766–779.

Feldstein, Martin S. (1969). The Effects of Taxation on Risk Taking. *Journal of Political Economy*, 77(5), 755–764.

Ferraro, Domenico and Vytautas Valaitis (2023). Wealth and Hours. Manuscript.

Floden, Martin and Jesper Lindé (2001). Idiosyncratic Risk in the United States and Sweden: Is There a Role for Government Insurance? *Review of Economic Dynamics*, 4(2), 406–437.

Fried, Stephie (2018). Climate Policy and Innovation: A Quantitative Macroeconomic Analysis. *American Economic Journal: Macroeconomics*, 10(1), 90–118.

Gomme, Paul, B. Ravikumar, and Peter Rupert (2011). The Return to Capital and the Business Cycle. *Review of Economic Dynamics*, 14(2), 262–278.

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Iván Werning (2022). Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages? *American Economic Review*, 112(5), 1437–74.

Hamilton, James D. (1983). Oil and the Macroeconomy since World War II. *Journal of Political Economy*, 91(2), 228–248.

Hamilton, James D. (2003). What is an oil shock? *Journal of Econometrics*, 113(2), 363–398.

Hassler, John, Per Krusell, and Conny Olovsson (2021). Directed Technical Change as a Response to Natural Resource Scarcity. *Journal of Political Economy*, 129(11), 3039–3072.

Havranek, Tomas and Ondrej Kokes (2015). Income Elasticity of Gasoline Demand: A Meta-Analysis. *Energy Economics*, 47, 77–86.

Heathcote, Jonathan, Fabrizio Perri, and Giovanni L. Violante (2010). Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967–2006. *Review of Economic Dynamics*, 13(1), 15–51. Special issue: Cross-Sectional Facts for Macroeconomists.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante (2017). Optimal Tax Progressivity: An Analytical Framework. *The Quarterly Journal of Economics*, 132(4), 1693–1754.

Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L Violante (2020). Presidential Address 2019: How Should Tax Progressivity Respond to Rising Income Inequality? *Journal of the European Economic Association*, 18(6), 2715–2754.

Heindl, Peter and Isabella Schulte (2017). Price and income elasticities of residential energy demand in Germany. *Energy Policy*, 102, 512–528.

Huggett, Mark (1993). The risk-free rate in heterogeneous-agent incomplete-insurance economies. *Journal of Economic Dynamics and Control*, 17(5), 953–969.

Imrohoroğlu, Ayşe (1989). Cost of Business Cycles with Indivisibilities and Liquidity Constraints. *Journal of Political Economy*, 97(6), 1364–1383.

Keane, Michael P. (2011). Labor Supply and Taxes: A Survey. *Journal of Economic Literature*, 49(4), 961–1075.

Kilian, Lutz (2008). The Economic Effects of Energy Price Shocks. *Journal of Economic Literature*, 46(4), 871–909.

Kilian, Lutz (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review*, 99(3), 1053–69.

Kim, In-Moo and Prakash Loungani (1992). The Role of Energy in Real Business Cycle Models. *Journal of Monetary Economics*, 29(2), 173–189.

Kimbrough, Gray (2019). Measuring commuting in the American Time Use Survey. *Journal of Economic and Social Measurement*, 44(1), 1–17.

Krueger, Dirk and Fabrizio Perri (2006). Does Income Inequality Lead to Consumption Inequality? Evidence and Theory1. *The Review of Economic Studies*, 73(1), 163–193.

Kuhn, Florian, Matthias Kehrig, and Nicolas L. Ziebarth (2021). Welfare Effects of Gas Price Fluctuations. Manuscript.

Kuhn, Moritz and José-Víctor Ríos-Rull (2016). 2013 Update on the U.S. Earnings, Income, and Wealth Distributional Facts: A View from Macroeconomics. *Quarterly Review*, 37(April), 1–75.

Känzig, Diego R. (2021). The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements. *American Economic Review*, 111(4), 1092–1125.

Labandeira, Xavier, José M. Labeaga, and Xiral López-Otero (2017). A Meta-Analysis on the Price Elasticity of Energy Demand. *Energy Policy*, 102, 549–568.

Langot, François, Selma Malmberg, Fabien Tripier, and Jean-Olivier Hairault (2023). The Macroeconomic and Redistributive Effects of Shielding Consumers from Rising Energy Prices: the French Experiment. CEPREMAP Working Papers (Docweb) 2205, CEPREMAP.

Matsuyama, Kiminori (2019). Engel's Law in the Global Economy: Demand-Induced Patterns of Structural Change, Innovation, and Trade. *Econometrica*, 87(2), 497–528.

McGrattan, Ellen R. and Edward C. Prescott (2003). Average Debt and Equity Returns: Puzzling? *American Economic Review*, 93(2), 392–397.

Metcalf, Gilbert E. (2008). An Empirical Analysis of Energy Intensity and Its Determinants at the State Level. *The Energy Journal*, 29(3), 1–26.

Mills, Edwin S. (1967). An Aggregative Model of Resource Allocation in a Metropolitan Area. *The American Economic Review*, 57(2), 197–210.

Montiel Olea, José L., James H. Stock, and Mark W. Watson (2021). Inference in Structural Vector Autoregressions identified with an external instrument. *Journal of Econometrics*, 225(1), 74–87. Themed Issue: Vector Autoregressions.

Muth, Richard F. (1969). *Cities and Housing: The Spatial Pattern of Urban Residential Land Use*. Chicago and London: The University of Chicago Press.

Nakamura, Emi and Jón Steinsson (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect*. *The Quarterly Journal of Economics*, 133(3), 1283–1330.

Pieroni, Valerio (2023). Energy Shortages and Aggregate Demand: Output Loss and Unequal Burden from HANK. *European Economic Review*, 154, 104428.

Ready, Robert, Nikolai Roussanov, and Ewelina Zurowska (2019). Why Does Oil Matter? Commuting and Aggregate Fluctuations. *Working Paper*.

Rouwenhorst, K. Geert (1995). *10 Asset Pricing Implications of Equilibrium Business Cycle Models*, pp. 294–330. Princeton: Princeton University Press.

Schwark, Florentine (2014). Energy Price Shocks and Medium-Term Business Cycles. *Journal of Monetary Economics*, 64, 112–121.

Stock, James H. and Mark W. Watson (2018). Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments. *The Economic Journal*, 128(610), 917–948.

Sue Wing, Ian (2008). Explaining the declining energy intensity of the U.S. economy. *Resource and Energy Economics*, 30(1), 21–49.

Trabandt, Mathias and Harald Uhlig (2011). The Laffer Curve Revisited. *Journal of Monetary Economics*, 58(4), 305–327.

APPENDIX A: MATHEMATICAL DERIVATIONS

A.1. Household Problem

The Lagrangian for a household is given by

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

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

The household first order conditions are:

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

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

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

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

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

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

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 μ_{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 μ_{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:

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

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

Firms in a perfectly competitive sector produce non-energy goods and maximize profits. With the output price normalized to 1, their profit maximization problem reads 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 μ_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 the interview survey data 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 CEX sample due to the termination of the variable representing 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 the CEX expenditure data with disaggregated regional quarterly price series from the BLS's Urban Consumer Price Index (CPI-U), which started in 1999. These data divide the U.S. into four broad regions: (i) northeast, (ii) midwest, (iii) south, and (iv) west. I match the expenditures in consumption categories with category-specific CPIs: for 'food at home', I use the CPI of 'food at home'; for 'food away from home', the CPI of 'food away from home'; for 'alcoholic beverages', the CPI of 'alcohol and beverages'; for 'natural/piped gas', the CPI of 'piped gas'; for 'electricity', the CPI of 'electricity'; for 'gasoline', the CPI of 'gasoline (general)'; for 'other fuel oils', the CPI of 'energy commodities'; for 'utilities other than energy', the CPI of 'utilities and fuels'; for 'shoes and other apparel', the CPI of 'apparel'; for 'vehicle purchases', the CPI of 'vehicle'; for 'other transportation', the CPI of 'transport'; for 'health', the CPI of 'medical care'; for 'entertainment, entertainment fees, and reading', the CPI of 'recreation'; for 'personal care items', the CPI of 'durables'; for 'education', the CPI of 'education and communication'; for 'tobacco', the CPI of 'nondurables less food, beverages, and apparel'; for 'housing', the CPI of 'shelter'; for 'furniture and fixtures', the CPI of 'furnishing operations'; for 'equipment' and 'maintenance and repair', the CPI of 'furnishing supplies'; for 'cash contributions', the CPI of 'overall services'; and finally, for 'domestic services', the CPI of 'professional services'.

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.

The CEX does not provide direct information on energy consumption for commuting to work. However, it reports household expenditures on gasoline and motor oil, including specific spending for long drives and vacations (see file **trv'yr'** in folder **expn'yr'**, available since 1994). To extract energy expenditures for commuting to work, I first 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 the log of after-tax income, the log of total household expenditure, quadratic time trends, and a binary dummy variable indicating households with zero earners.[29] The coefficient of the dummy variable represents the percentage change in gasoline expenditures between employed and non-employed households. I then use that coefficient to obtain employed households' energy expenditure for commuting to work. The remaining gasoline expenditures are merged with the residential energy expenditures.

For the analysis in Section 3.4, I include households with reference persons aged 25 to 64 who participated in four interviews between 2021:Q1 and 2022:Q2. I use the variable **inc_rank** to classify households. The classification is mainly based on the income rank in

29. This regression is similar to the one used by Aguiar and Bils (2015) to adjust food at home expenditures for the waves from 1982 to 1987 due to a change in the CEX questionnaires during those years. For this adjustment, they use data from 1980 to 1989 and regress the log of food at home expenditure on the log of after-tax income, the log of total expenditure, quadratic time trends, and a binary dummy variable that equals one for the waves from 1982 to 1987.

the first interview. If households in their first interview report zero or negative pre-tax income, I use the imputed income rank (`inc_rnkm`) for those households. I drop households with annual pre-tax income between zero and one thousand dollars.

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. The PSID is a longitudinal study 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 biennially 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. My main interest lies in variables related to net wealth, employment, and earnings. Wealth is defined as total household assets minus total liabilities. Assets in PSID include the home, the value of the farm or business, other real estate assets, the value of the checking or savings accounts, stock holdings, vehicles, annuity IRA accounts, and other assets, while the liabilities include mortgage, farm/business debt, other real estate debt, credit card debt, student loan debt, medical debt, family loan debt, legal debt, and other debt.

Since the PSID records labor market variables from the previous year, I use waves from 2001 to 2015 for labor market-related variables, such as employment and earnings, and waves from 1999 to 2013 for wealth. In all cases, the sample is restricted to households with heads aged 25 to 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 (ω_{iERt}) and non-energy (ω_{iCt}) goods:

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

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 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. ζ_{iER} accounts for relative taste parameter, $\zeta_{iER} \equiv \ln\left(\Omega_{iER}/(\Omega_{iC}=1)\right)$, and ε_{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, $\zeta_{iER} = \beta'\mathbf{Z}_i + \nu_{ERr}$. This assumption imposes the constraint that the cross-household heterogeneity in the time-invariant taste parameter can be fully explained as a linear function of the

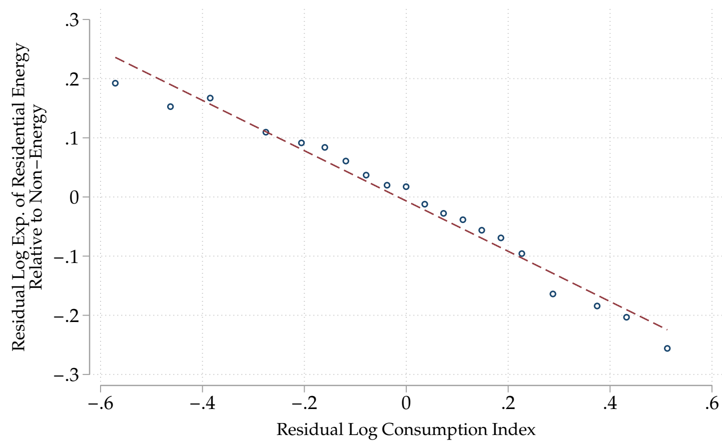


FIGURE C.1
PARTIAL CORRELATION OF THE LOG CONSUMPTION INDEX AND LOG EXPENDITURE SHARE OF ENERGY RELATIVE TO NON-ENERGY

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.

vector $\boldsymbol{Z}_i$ 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, ε_{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 address 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 household income quintile, 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 Hausman-style relative prices, 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 con-

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

Consumption Category	CE Share (in Percentage)	Nonhomothetic CES ϵ_j	Nonhomothetic CES η_j	Reduced-Form η_j
Residential Energy	7.94	0.346*** (0.020)	0.522	0.466*** (0.007)
Non-Energy	92.06	1.00 (-)	1.041	0.989*** (0.005)

Note. The structural estimation of η_j uses $\sigma = 0.248$ as the elasticity of substitution between residential 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. Abbreviations: CE, Expenditure on Consumption Basket; CES, Constant Elasticity of Substitution.

structed 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.

To validate the demand estimation presented in Table 2, I compare the structurally estimated expenditure elasticities with their reduced-form counterparts.[30] For the reduced-form estimation, I follow the approach proposed by Aguiar and Bils (2015). Denoting a household by i, I estimate the expenditure elasticity of consumption good j, η_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, α_{jtr} captures time and region fixed effects, Exp^i_t represents total quarterly expenditure of household i, $\mathbf{Z}^i$ is 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

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

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, placing 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 productivity 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 λ 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(a)-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 λ, and repeat the process until the government budget is balanced. For this step, I also use a root finding algorithm.

D.2. Calibration

First, make a guess for the set of endogenous parameters and solve for the steady state equilibrium using the algorithm described in Appendix 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 Appendix D.1, update the guess for 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 Appendix 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. Guess a sequence of government budget balancing parameter $\{\lambda_t\}_{t=1}^{T-1}$.
5. 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.
6. Starting from the initial steady state distribution $\Gamma^\star$, simulate the distribution Γ 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 Appendix D.1.
7. Check if the net revenue to GDP ratio remains constant throughout the transition path. If so, 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 λ, then return to step 5 and repeat the process until the convergence criterion is met. In practice, I compare the current sequence of λ with the implied sequence to check for convergence.
8. 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.
9. Once the solution is obtained, check whether T is sufficient by increasing T and evaluating if there are any significant changes in transition dynamics.

Appendix E: An Example of Energy Price Shock Impact

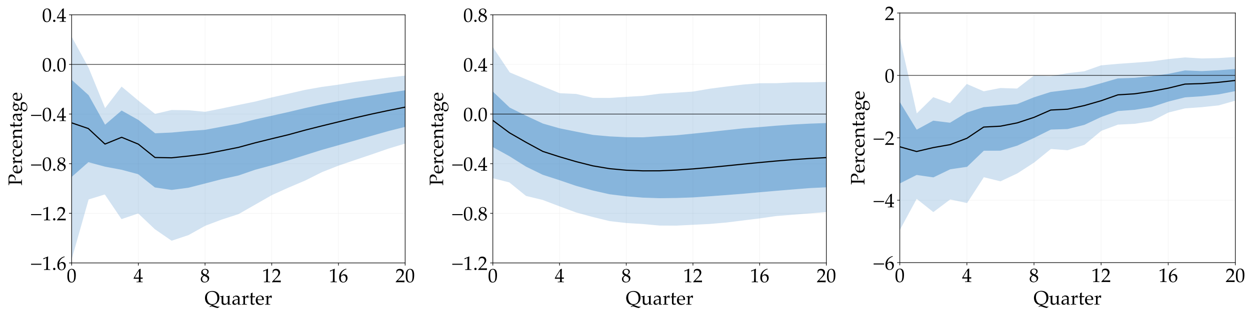
In this section, I empirically examine the impact of an oil price shock on consumption. The focus on oil price shock stems from two main reasons. First, there exist well-identified instruments for oil price shocks. Second, oil price shocks are one of the main drivers of broader energy price shocks. I 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).[31] Following that model, 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.[32] 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

31. 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.

32. 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.

(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^{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.

Consumption Responses. Figure E.1 shows that an inflationary oil price shock significantly impacts both household and firm energy consumption.[33] It leads to a reduction

33. Firm energy consumption includes energy consumption of the commercial and industrial sectors, as

in household energy consumption, non-energy consumption, and firms' energy consumption. Although the response of household non-energy consumption is slightly less 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 over a long period makes it challenging to precisely estimate the responses of such shocks for different income groups empirically.

APPENDIX F: CALIBRATION SUPPLEMENT

F.1. *Summary of Baseline Calibration*

In Section 5, I describe the baseline calibration strategies. Table F.1 presents the externally assigned and estimated parameter values, and Table F.2 provides an overview of the internal calibration strategy and the calibrated parameters.

F.2. *Calibration of Alternative Models*

In addition to the baseline model, I calibrate four other versions. The external parameters in these models are set to the values of the baseline version whenever possible, and the internal calibration strategies closely follow the procedure described in Section 5. Table F.4 presents the internally calibrated parameters, and Table F.5 shows the model fit in terms of targeted moments for all four models.

(i) **Homothetic Consumption Preferences.** Unlike the baseline model, consumption preferences are now assumed to be homothetic, meaning ϵ_C and ϵ_{E_R} are set to 1.00.

(ii) **No Energy in Production.** In this version of the model, firms use a Cobb-Douglas production technology that requires only capital and labor as inputs, meaning energy is not used as one of the factor inputs.

(iii) **Full Employment.** This version of the model considers only the intensive margin of labor supply choice. Since there is no unemployment, I shut down the mean-tested transfer and use the measure of earnings tax progressivity from Heathcote,

reported by the U.S. EIA.

TABLE F.1
EXTERNALLY SET AND ESTIMATED PARAMETERS

Parameter	Description	Value	Source
Technology parameters:			
α	Output elasticity of capital	0.36	Literature
δ	Depreciation rate of capital	0.015	Literature
Idiosyncratic labor productivity parameters:			
ρ_z	Persistence of productivity shocks	0.975	Floden and Lindé (2001)
σ_z	Standard deviation of productivity innovations	0.165	Floden and Lindé (2001)
Preference parameters:			
γ	Risk aversion coefficient	2.0	Literature
σ	ES between energy and non-energy consumption goods	0.248	Demand estimation (column 4 of Table 2)
ϵ_{E_R}	Non-homotheticity parameter of energy consumption	0.346	Demand estimation (column 4 of Table 2)
ϵ_C	Non-homotheticity parameter of non-energy consumption	1.0	Normalization
Ω_C	Weight of non-energy goods in the consumption basket	1.0	Normalization
ν	Frisch elasticity of labor supply	0.50	Literature
Tax & transfer parameters:			
τ^a	Capital income tax rate	0.36	Trabandt and Uhlig (2011)
τ^l	Curvature of the earnings tax function	0.09	Heathcote, Storesletten, and Violante (2020)

Note. Abbreviation: ES, Elasticity of Substitution.

Storesletten, and Violante (2017), which accounts for transfers.

(iv) **No Commuting Costs.** This version of the model does not explicitly feature commuting costs. Instead, it merges commuting and residential energy consumption into a single energy good, which households combine with the non-energy good to derive utility. The baseline values of the elasticity of substitution between the energy and non-energy goods and the non-homotheticity parameter of the energy good are changed to the values in Table F.3. The calibration target for the weight of energy consumption in the household consumption basket is now set to 0.098.

TABLE F.2
INTERNALLY CALIBRATED PARAMETERS

Parameter	Description	Value	Target
Technology parameters:			
κ	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	20.850	Wealth share of top wealth decile (66.44%)
π_{up}	Probability of transitioning from z to z_{max}	7.033×10^{-4}	Earnings share of top earnings decile (35.04%)
π_{stay}	Probability of remaining at z_{max}	0.978	Earnings share of top 1% of the earnings distribution (11.62%)
Preference parameters:			
β	Discount factor	0.981	After-tax rate of return (4.1%)
Ω_{E_R}	Weight of E_R in the consumption basket	0.080	Average expenditure share of E_R in consumption basket (7.94%)
φ_1	Determinant of the utility cost of intensive margin labor supply	38.839	Employed households' average share of hours worked (33.33%)
φ_2	Fixed utility cost of working	0.523	Employment rate (79.63%)
Tax & transfer parameters:			
λ	Government budget balancer	0.789	Government purchases as a share of GDP (20.0%)
$\bar{e}$	Maximum possible lump-sum transfer	0.238	Average transfers-to-earnings ratio of the lowest wealth quintile (14.72%)
Other parameters:			
ι_0	Scaling factor for E_T	0.024	Employed households' average expenditure share on E_T (2.00%)
ι_1	Sensitivity of E_T to household income	0.579	Bottom-to-top income quintile workers' expenditure share on E_T (1.37)
$\underline{a}$	Borrowing limit	-0.067	Share of households with negative wealth (12.58%)

Note. Abbreviation: GDP, Gross Domestic Product.

TABLE F.3
DEMAND ESTIMATION: COMBINING RESIDENTIAL AND COMMUTING ENERGY INTO A SINGLE CATEGORY

Parameter	(1)	(2)	(3)
σ	0.237***	0.264***	0.239***
	(0.014)	(0.013)	(0.019)
ϵ_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 (≤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.

TABLE F.4
INTERNALLY CALIBRATED PARAMETERS OF ALTERNATIVE MODELS

Parameter	Homothetic Cons. Preferences	No Energy in Production	Full Employment	No Commuting Costs
Technology parameters:				
κ	20.0	-	20.0	20.0
Idiosyncratic labor productivity parameters:				
$z_{\max}$	20.842	21.602	23.195	23.541
π_{up}	6.748×10^{-4}	6.328×10^{-4}	7.780×10^{-4}	6.206×10^{-4}
π_{stay}	0.978	0.979	0.982	0.978
Preference parameters:				
β	0.981	0.981	0.982	0.981
Ω_{E_R}	0.100	0.082	0.089	0.101
φ_1	37.467	37.319	24.710	40.515
φ_2	0.549	0.556	-	0.598
Tax & transfer parameters:				
λ	0.789	0.808	0.849	0.789
$\bar{e}$	0.227	0.260	-	0.238
Other parameters:				
ι_0	0.024	0.025	0.033	-
ι_1	0.593	0.590	0.813	-
$\underline{a}$	-0.066	-0.045	-0.037	-0.075

Note. Abbreviation: Cons., Consumption.

TABLE F.5

FIT OF ALTERNATIVE MODELS: TARGETED MOMENTS

Moment	Data	Homothetic Cons. Preferences	No Energy in Production	Full Employment	No Commuting Costs
Firms' expenditure on energy as a share of GDP	4.10%	4.10%	-	4.10%	4.10%
Wealth share of top wealth decile	66.44%	64.94%	64.63%	66.63%	65.06%
Earnings share of top earnings decile	35.04%	35.36%	34.73%	37.49%	35.00%
Earnings share of top 1% of the earnings distribution	11.62%	14.25%	13.77%	12.75%	14.26%
After-tax rate of return	4.10%	4.13%	4.13%	4.10%	4.12%
Average expenditure share of E_R in consumption basket	7.94%	7.94%	7.94%	7.94%	-
Average expenditure share on energy ($E_R + E_T$)	9.80%	-	-	-	9.80%
Employed households' average share of hours worked	33.33%	33.34%	33.33%	33.32%	33.34%
Employment rate	79.63%	79.83%	0.556	-	80.57%
Government purchases as a share of GDP	20.0%	20.05%	20.00%	20.00%	20.00%
Average transfers-to-earnings ratio of the lowest wealth quintile	14.72%	15.90%	13.25%	-	14.56%
Employed households' average expenditure share on E_T	2.00%	2.00%	2.00%	2.01%	-
Bottom-to-top income quintile workers' expenditure share on E_T	1.37	1.37	1.37	1.37	-
Share of households with negative wealth	12.58%	10.53%	14.33%	12.75%	10.35%

Note. The table presents targeted moments of calibrated alternative models along with their empirical counterparts. All model moments are computed in steady state. Abbreviation: Cons., Consumption.

APPENDIX G: ADDITIONAL TABLES AND FIGURES

TABLE G.1
EXPENDITURE SHARES AND EXPENDITURE ELASTICITIES OF CONSUMPTION CATEGORIES

		Nonhomothetic CES		Reduced-Form
Consumption Category	CE Share (in Percentage)	ϵ_j	η_j	η_j
Energy	9.80	0.383*** (0.020)	0.549	0.489*** (0.007)
Non-Energy	90.20	1.00 (-)	1.049	0.989*** (0.005)

Note. The structural estimation of η_j uses $\sigma = 0.239$ as the elasticity of substitution between energy (residential+commuting) 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. Abbreviations: CE, Expenditure on Consumption Basket; CES, Constant Elasticity of Substitution.

TABLE G.2
ESTIMATES OF AR(1) ENERGY PRICE PROCESS

	Energy CPI Deflated by All Less Energy CPI		Average Energy Price Deflated by GDP Deflator	
Parameter	OLS	MLE	OLS	MLE
		Panel A: Full Sample		
ρ_{pE}	0.966 (0.017)	0.962 (0.016)	0.966 (0.015)	0.983 (0.012)
σ_{pE}	0.046 (0.002)	0.046 (0.002)	0.055 (0.003)	0.056 (0.003)
		Panel B: 1975-2020		
ρ_{pE}	0.956 (0.022)	0.953 (0.021)	0.957 (0.020)	0.964 (0.018)
σ_{pE}	0.052 (0.003)	0.052 (0.003)	0.056 (0.003)	0.057 (0.003)

Note. The table presents estimates of AR(1) energy price process using different methods and data. The full sample of "Energy CPI Deflated by All Less Energy CPI" comprises quarterly data from 1957 to 2022, while "Average Energy Price Deflated by GDP Deflator" comprises quarterly data from 1970 to 2020, which is interpolated from yearly average energy price data from the U.S. Energy Information Administration. Standard errors are shown in parentheses. Abbreviations: CPI, Consumer Price Index; GDP, Gross Domestic Product; OLS, Ordinary Least Squares; MLE, Maximum Likelihood Estimation.

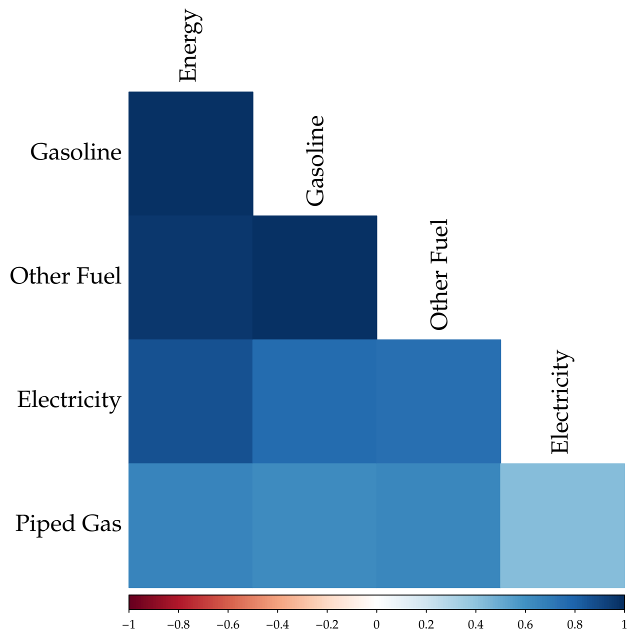


FIGURE G.1
CORRELATION MATRIX OF CPIS OF DIFFERENT ENERGY GOODS

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.

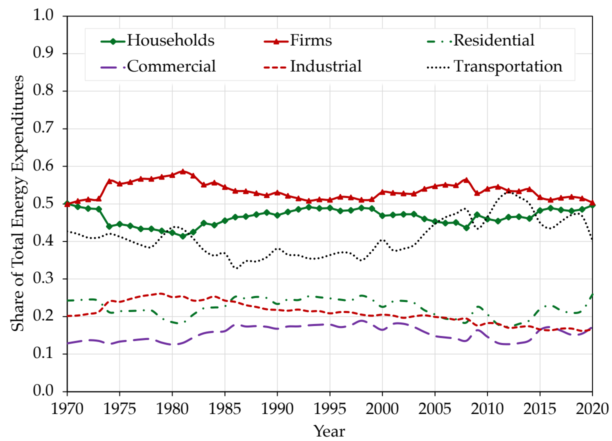


FIGURE G.2
PATTERNS OF ENERGY CONSUMPTION EXPENDITURES

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

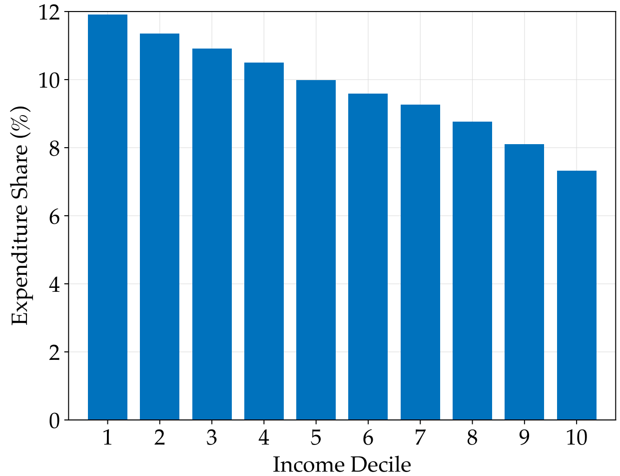


FIGURE G.3
DISTRIBUTION OF HOUSEHOLD EXPENDITURE SHARE ON ENERGY

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.

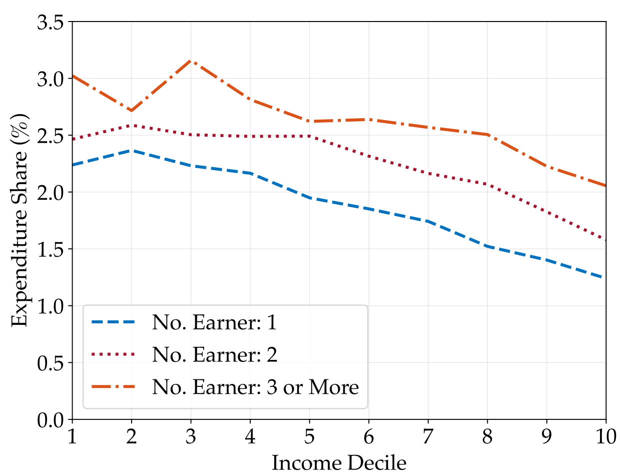
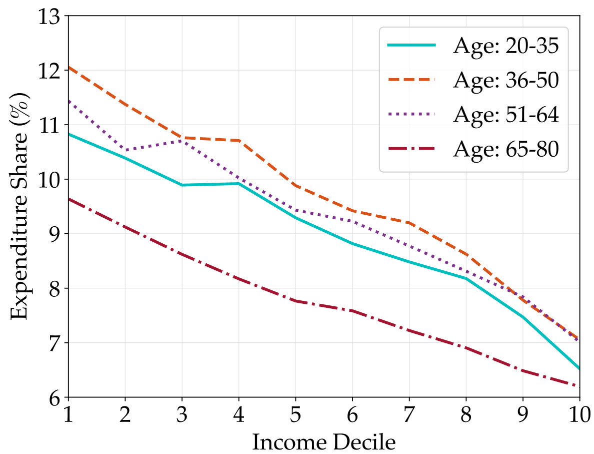
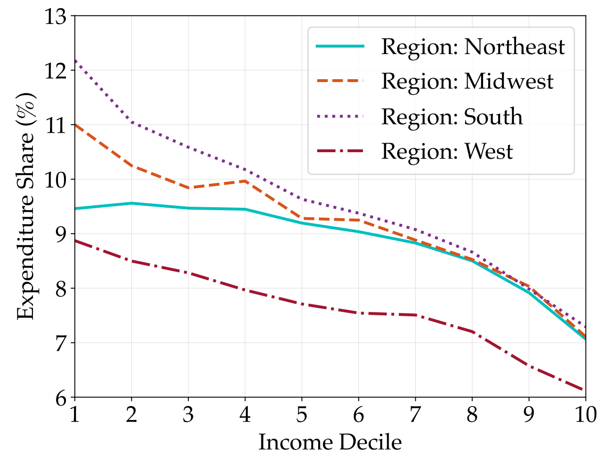


FIGURE G.4
DISTRIBUTION OF HOUSEHOLD EXPENDITURE SHARE ON COMMUTING ENERGY BY NUMBER OF EARNERS

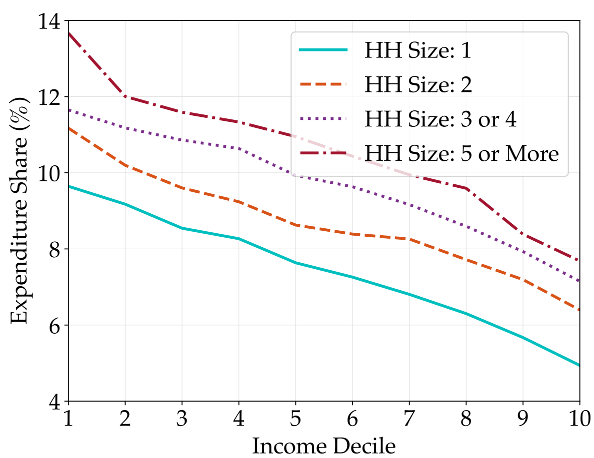
Note. The figure plots the household expenditure shares on commuting energy across income deciles by the number of earners in a household, using data from the quarterly waves of the CEX from 1999 to 2013. *Commuting energy* refers to the energy used to commute to work.



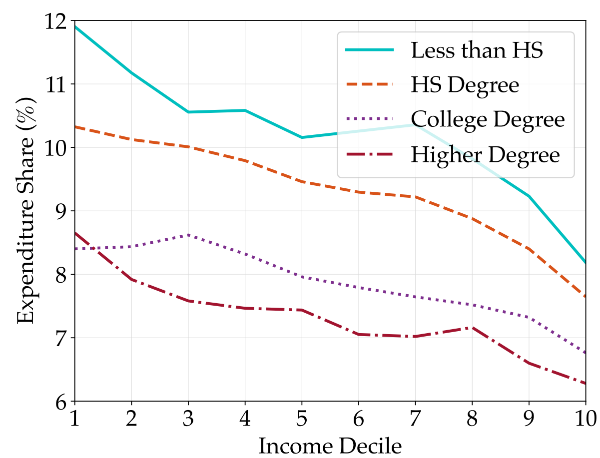
(A) Energy Expenditure Share
(By Age Group)



(B) Energy Expenditure Share
(By Region)



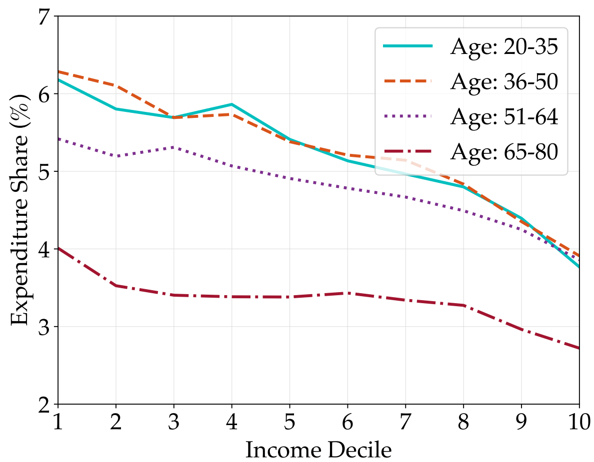
(C) Energy Expenditure Share
(By Household Size)



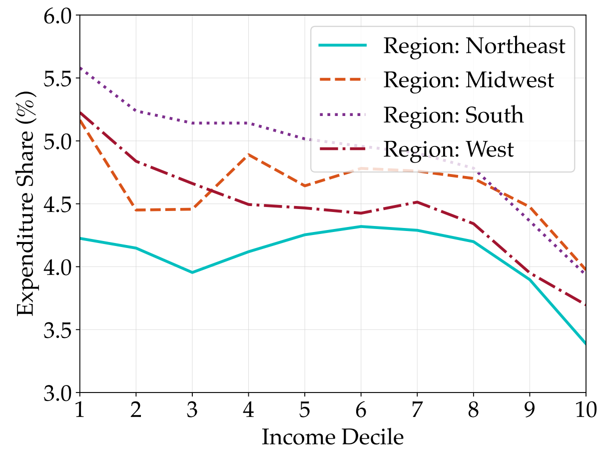
(D) Energy Expenditure Share
(By Education Group)

Figure G.5
Expenditure Share on Energy by Demographics

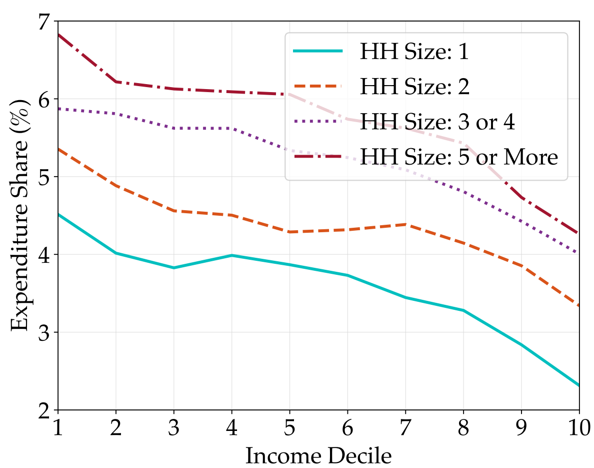
Note. The figure plots the household energy expenditure shares across income deciles by different demographic groups—age, region, household size, and education level—using the quarterly waves of CEX from 1994 to 2019. It includes all forms of household energy spending, such as electricity, piped gas,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



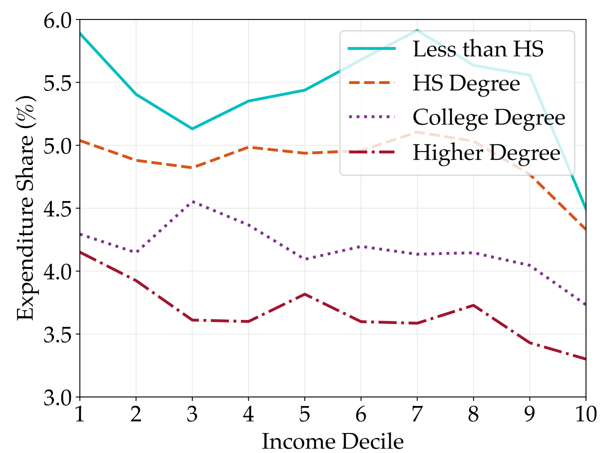
(A) GASOLINE EXPENDITURE SHARE
(BY AGE GROUP)



(B) GASOLINE EXPENDITURE SHARE
(BY REGION)



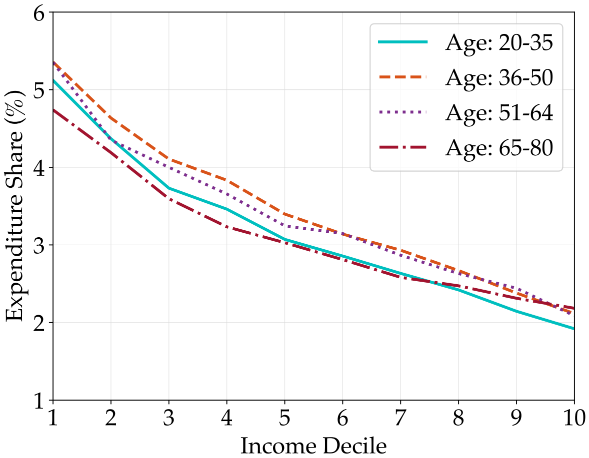
(C) GASOLINE EXPENDITURE SHARE
(BY HOUSEHOLD SIZE)



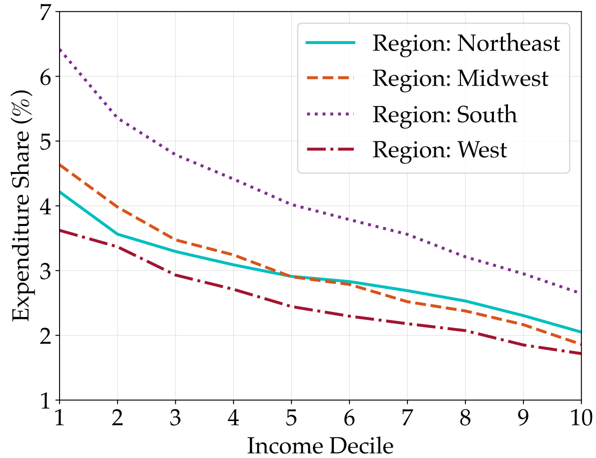
(D) GASOLINE EXPENDITURE SHARE
(BY EDUCATION GROUP)

FIGURE G.6
EXPENDITURE SHARE ON GASOLINE BY DEMOGRAPHICS

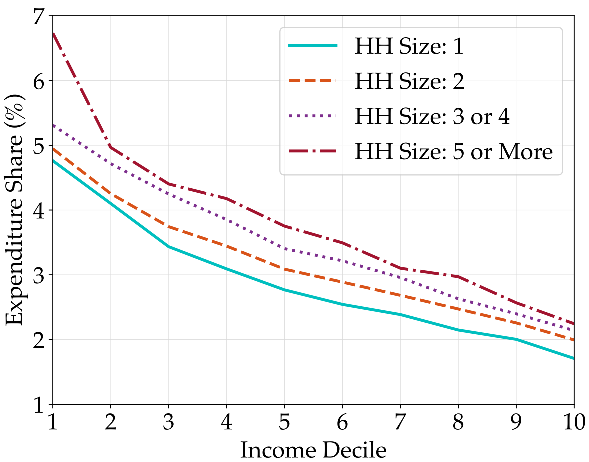
Note. The figure plots the household gasoline expenditure shares across income deciles by different demographic groups—age, region, household size, and education level—using the quarterly waves of CEX from 1994 to 2019.



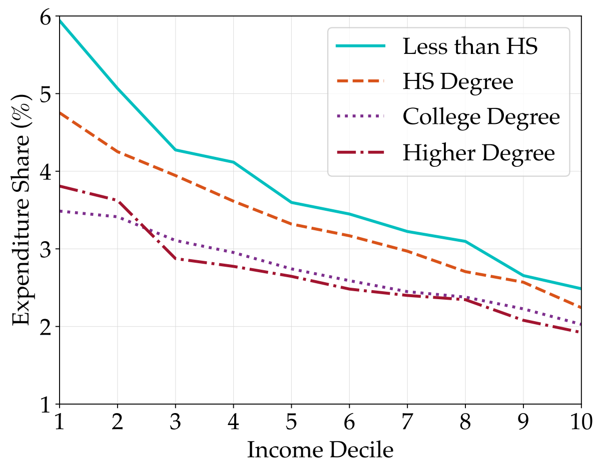
(A) ELECTRICITY EXPENDITURE SHARE
(BY AGE GROUP)



(B) ELECTRICITY EXPENDITURE SHARE
(BY REGION)



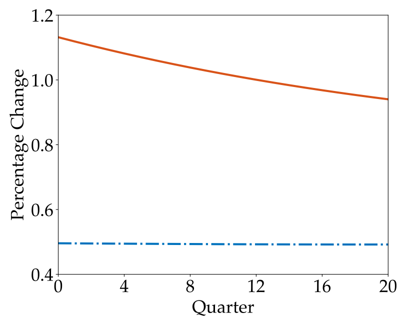
(C) ELECTRICITY EXPENDITURE SHARE
(BY HOUSEHOLD SIZE)



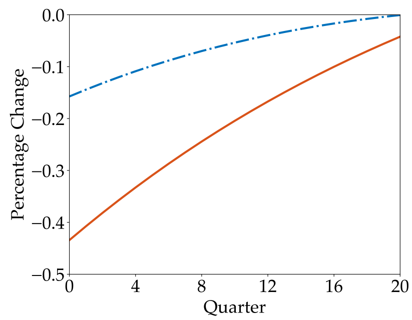
(D) ELECTRICITY EXPENDITURE SHARE
(BY EDUCATION GROUP)

FIGURE G.7
EXPENDITURE SHARE ON ELECTRICITY BY DEMOGRAPHICS

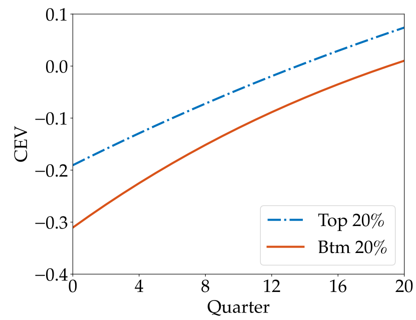
Note. The figure plots the household electricity expenditure shares across income deciles by different demographic groups—age, region, household size, and education level—using the quarterly waves of CEX from 1994 to 2019.



(A) HOURS WORKED (h_t)



(B) CONSUMPTION BASKET ($\boldsymbol{x}_t$)



(C) WELFARE

FIGURE G.8

RESPONSES TO A ONE STANDARD DEVIATION INFLATIONARY ENERGY PRICE SHOCK IN A FULL EMPLOYMENT MODEL FIXING ENERGY USE FOR COMMUTING AT THE PRE-SHOCK STEADY STATE LEVEL