(In)justices in Energy Pricing Schedules: Revealed Preferences Approach

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Abstract

How do household energy consumption preferences shift in response to changing energy pricing schedules under the pressures of energy transition, market fluctuations, and energy subsidies? We implement an advanced non-parametric test for analyzing the Random Utility Model of household energy consumption to compare preferences for prices across various use cases (Deb et al., 2023). Our aim is to estimate the effects of changing price schedules for different energy sources across socioeconomic groups to determine whether these changes lead to equitable improvements in household welfare. For this purpose, we compare the 2015 and recently released 2020 rounds of Residential Energy Consumption Survey (RECS) using a representative sample of U.S. households microdata.

Our estimates reveal a general preference for the 2020 price schedule among all households as compared to 2015. However, this preference is less pronounced among energy-burdened groups, suggesting that the pricing adjustments, particularly in electricity, disproportionately benefit wealthier households. For example, the breakdown by racial background shows that the 2020 schedule with 5% decrease in electricity price and 16% increase in natural gas price is preferred by 75% of White households. This number is only 65% for Black and Hispanic households, while the 2020 prices seem more beneficial both in absolute and percentage differences (-7% and 5% respectively).

This suggests that although the 2020 energy pricing schedule was generally favorable, it may not have sufficiently addressed energy burdens experienced by the most financially constrained households. This observation is particularly puzzling given the presence of federal and state programs intended to reduce energy insecurity for low-income households (Memmott et al., 2021; Murray and Mills, 2014; Carley and Konisky, 2020). These findings could support arguments for more nuanced energy pricing policies that take into account the economic disparities among different demographic groups, similar to the perspectives put forward by scholars of energy poverty (Drehobl, Ross and Ayala, 2020; Hernández, 2016; Brown et al., 2020; Bednar, Reames and Keoleian, 2017; Graff, 2024).

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1 Introduction

1.1 Aim and Scope

If prices for energy sources change nonlinearly and in different directions, which can often be the case when a particular subsidy is implemented, determining which price schedule is most beneficial for consumers becomes difficult [1]. Traditional analyses in this direction focus primarily on monetary gains and losses from the subsidies, but this approach may not fully capture consumer preferences. The aim of the paper is to analyze how households from different socioeconomic backgrounds respond to existing changes in energy prices, focusing on the period between 2015 and 2020 across four US CENSUS regions (Northeast, Midwest, South, West).

We examine whether households show a ***preference*** for energy pricing in one energy schedule over the other. By doing so, we aim to better understand consumption preferences for water and space heating powered by electricity or gas— which are the main expenses in a household energy budget (EIA, 2023) — and how these ***revealed preferences*** inform us about the distributional effects of energy pricing and subsidy policies across diverse segments of the US population.

Since in most homes heating and cooling equipment accounts for the largest amount of energy consumption, revealing consumers' preferences for different pricing schedules is crucial. [2] With the exacerbated effects of climate change and the future energy transition towards electrification, energy demand and prices are expected to fluctuate more (van Ruijven, De Cian and Sue Wing, 2019; Yu and Kittner, 2024). This can disproportionately affect the most vulnerable populations, particularly lower-income households that are already energy burdened by heating and cooling costs. [3]

1.2 What are the Revealed Preferences?

Revealed preferences in this context refer to the choices consumers make under different energy pricing schedules, observed directly from their consumption behavior as captured in the Residential Energy Consumption Survey (RECS) data from the 2015 and 2020 iterations. These preferences reveal who benefits from current energy pricing policies and who does not, particularly among groups segmented by levels of poverty, racial and ethnic backgrounds, education, and recipients of energy subsidies—LIHEAP.

We perceive the effects of pricing schedules through the lens of distributive politics literature (Jenkins et al., 2020; Aklin, 2023). Specifically, distributional effects from energy prices and subsidies refer to the unequal impacts these policies have on different households (Jenkins et al., 2016). Some households benefit from more favorable access to energy resources and stable pricing, while others are more adversely affected, for example, during extreme weather conditions such as very hot or very cold days (Yu and Kittner, 2024). Simply put, the future of household-level distributional effects is highly uncertain due to factors such as climate change, energy transition and market, and poorly designed assistance programs.

[1] Consider, for example, two price schedules. The price for electricity is higher and for gas is lower in the former, while the opposite is true for the latter. Then, even if consumption decisions are known, there is no straightforward way to tell if the consumer better off as the change from one budget constraint to the other can induce movement downwards and upwards the levels of utility

[2] In 2022, the residential sector accounted for about 15% of total U.S. natural gas consumption, with natural gas being the source of about 42% of U.S. residential sector end-use energy consumption. Approximately 60% of U.S. homes use natural gas for space and water heating, cooking, and drying clothes (EIA, 2023).

[3] The Low Income Home Energy Assistance Program (LIHEAP), the largest component of federally sponsored energy subsidy programs, has traditionally focused on heating and cooling payment assistance, accounting for almost 80% of the benefits provided to households.

The preferences we are examining include choices related to energy consumption under different pricing schedules for electricity and natural gas. Specifically, we are interested in understanding how households allocate their energy usage between these two sources under varying cost structures. The price schedule here is nothing more than a set of 4 prices: price of 1 Btu generated by electricity for space heating, price of 1 Btu generated by electricity for water heating, price of 1 Btu generated by natural gas for space heating, and price of 1 Btu generated by natural gas for water heating. A preference for one schedule over the other means, for instance, a household deciding to use more natural gas for heating if its price is lower compared to electricity, or vice versa. These choices are crucial as they reflect the underlying preferences and constraints different socioeconomic groups face. By analyzing these consumption patterns, we aim to uncover how changes in energy prices impact household welfare and whether these impacts are equitably distributed. This analysis is particularly relevant in the context of recent price adjustments and energy subsidy policies, which have significant implications for energy justice and the equitable distribution of energy resources.

In practical terms, having certain preferences means that a household chooses one energy pricing schedule over another based on a variety of factors that influence their consumption decisions. These factors can include the overall cost of energy, the reliability and availability of energy sources, and the specific energy needs of the household. However, our claim is that most of it is reflected by changes in the 4 prices we focus on. For example, a household might prefer a pricing schedule with lower electricity rates if they rely heavily on electric heating and appliances. Conversely, a household that uses natural gas for water heating may clearly favor a pricing schedule that offers more favorable natural gas rates. These preferences are not just about the immediate financial costs but also about long-term savings, convenience, and the potential impact on household comfort and quality of life. By examining these choices, we can gain insights into the broader implications of energy pricing policies and how they affect different demographic groups, particularly in terms of energy affordability and access.

1.3 Context of Energy Pricing Schedules

Historically, the design and implementation of assistance programs, whether manifested as price assistance (e.g., Medicaid, the Low Income Home Energy Assistance Program), efficiency programs (such as the Weatherization Assistance Program), or rebates (Home Efficiency Rebates programs), have remained subjects of debate among both political scientists and policymakers (Pierson, 1994; Soss, 1999; Allan and Scruggs, 2004; Sovacool and Dworkin, 2015; Murray and Mills, 2014). Economic and political science research has shown a concerning trend: bills and price assistance, while well-intentioned, tend to disproportionately benefit high or middle-income households (Graff and Pirog, 2019; Borenstein and Davis, 2016; Tonn, Rose and Hawkins, 2018; Reames, Reiner and Stacey, 2018). This unintentionally burdens low-income households, exacerbating the issues these subsidies aim to address.

Recent academic discussion of energy justice considerations has shown that a reevaluation of offered programs is required (Sovacool and Dworkin, 2015; Owen and Barrett, 2020; Jenkins et al., 2020, 2016). Yet, research considering energy justice framework and demographic disparities in the energy pricing schedules is limited. We aim to close this gap by analyzing how different demographic segments react to existing energy policies, thus informing more equitable and impactful price adjustments policies.

Applying the revealed preference approach, particularly in the context of energy consumption and pricing, is a challenging task when done on cross-sectional data. The difficulties arise from the inherent variability in consumer behavior, the influence of numerous socioeconomic factors, and the need for granular data at the micro-level. This is compounded with the fact that testing for rationalizability of preference profiles is essentially an NP-hard problem (Smeulders, Cherchye and

De Rock, 2021). Moreover, while numerous studies have analyzed revealed preferences in other domains, applying these methods to energy microdata is novel and significantly more complicated due to the lack of previous frameworks that account for the interaction between the energy source and application that energy is used for. Our study leverages advanced non-parametric estimation techniques and incorporates into population breakdowns the considerations of energy justice, an often overlooked aspect in traditional economic analyses.

Recently, there have been several successful forays into developing econometric tools to fill the need for recovering preferences in challenging situations like ours(Kitamura and Stoye, 2018; Deb et al., 2023). In particular, the use of Revealed Preference Models showed successful results in estimating the effects of altering healthcare subsidies on consumer decisions, surplus, and government spending (Tebaldi, Torgovitsky and Yang, 2023). Therefore, these methods exhibit significant potential for exploring other policies, such as energy subsidies.

Finally, a central issue in policy analysis is the determination of the welfare effect of price changes induced by the subsidy (Tebaldi, Torgovitsky and Yang, 2023; Deb et al., 2023). Since our primary focus is on energy poverty, the main counterfactual we consider, which has practical policy implications, is a targeted decrease in post-subsidy prices for low-income households consuming a particular energy source and using cooling & heating appliances. From consumers' perspective, this change can be interpreted as an increase in subsidy amount or a higher income cutoff for a tiered subsidy program. We also estimate substitution patterns of more uniform changes by considering situations in which subsidy is not targeted at a particular income group, energy source, or demographic. Most of these counterfactuals concern policy and regulatory design as targeted energy subsidies become more and more common. A great example of the increasing spread of such policies is the Inflation Reduction Act that includes rebates for energy efficiency and electrification (Offutt, 2023). Our estimates provide a transparent way to establish bounds on the effectiveness of such targeted programs while addressing the issues of potential deadweight loss (Polyakova and Ryan, 2019), social welfare, and energy poverty among low-income households.

This study contributes to the ongoing discussion on energy justice and the design of assistance programs. By evaluating the impacts of current energy prices through the lens of revealed preferences, we provide insights that could inform policymakers for a need of more equitable subsidy allocation, particularly as the energy transition shifts from gas to electricity as the primary energy source. The revealed preferences allow us to inform policymakers struggling with solving energy poverty. Our study shows that policymakers have to develop more equitable energy policies that address the needs of vulnerable populations and ensure fair access to energy resources as they make decisions about who receives policy benefits and who does not.

2 Theory

The dynamic theory of existential politics has been primarily applied to owners of assets like firms and states (Colgan, Green and Hale, 2021). However, the broader population will also face distributive effects from climate policy and energy transition. We are puzzled by the highly ineffective price adjustment policies and the lack of official recognition of the issues surrounding energy poverty (Bednar and Reames, 2020).

In our theory, we aim to develop predictions for different households operating under the relative uncertainty of the extent of price effects impacted by climate change, energy transition, market fluctuations and subsidies. The energy transition will take years, and its consequences will be long-term. The changes in price schedules influenced by climate change, price adjustments (such as energy subsidies), and other factors will have effects on the general population that are hardly quantifiable. The Figure 1 aims to illustrate how preferences are related to energy politics and the resultant distributive effects on different household demographics. The effects are still clear as reported by scholars: the overall outcome is energy poverty (Drehobl, Ross and Ayala, 2020). The solutions lie in effective price adjustments which can take the form of subsidies.

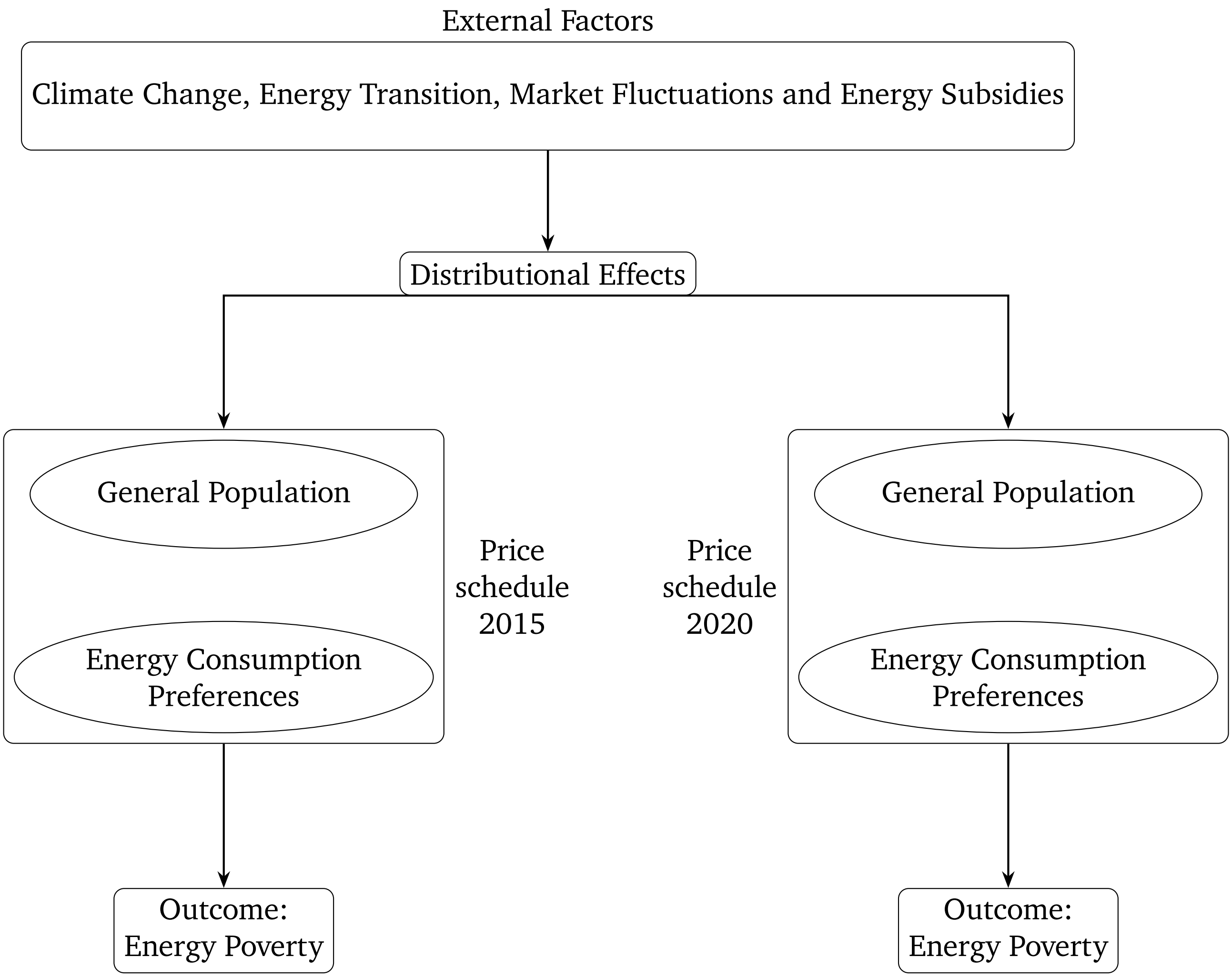

Figure 1: The Dynamic Effects of Energy Pricing on Household Consumption Preferences in 2015 and 2020

3 Literature review

3.1 Solving Energy Poverty with Subsidies

3.1.1 What is Energy Poverty?

Scholars have broadly defined energy poverty as the inability of a household to meet their basic energy needs (Bednar and Reames, 2020). This inability takes two forms: households and individuals finding energy either too costly to use or entirely unavailable(Aklin, 2023). Thus, energy poverty has two components: physical access to energy and the inability to afford adequate consumption of energy. However, there is no universally accepted definition of energy poverty or energy insecurity, as scholars tend to use different thresholds and values to identify populations burdened by energy costs.

An earlier definition from the 1980s, known as 'fuel poverty,' included U.K. households whose expenditure on all energy services exceeded 10% of their income (Boardman, 2009). The U.K. was the first country in the world to define what a fuel-poor household is[4] and analyze the prevalence of the problem across the country (Bednar and Reames, 2020). But critics argued that focusing solely on expenditure fails to consider the actual heating needs within households. Therefore, the definition of energy poverty should also include assessments of whether, for example, household health is protected through adequate thermal comfort, or sufficient lighting, cooking facilities, and typical appliance use (Moore, 2012).

There are two ways to measure energy poverty. It can be calculated objectively, for example, by measuring the amount of income a household spends on energy. (Hernández, Aratani and Jiang, N.d.) categorize households as insecure when their energy spending exceeds 10 percent of income. Alternatively, it can be measured subjectively by asking about a household's physical energy insecurity or the behavioral tactics they employ to manage their thermal environment, such as using space heaters or stoves (Hernández, 2016). Both measures—the amount of income spent on energy and subjective behavioral indicators—can be telling about the overall energy burden of households.

In the US, households are typically considered energy burdened if they spend more than 6% of their annual gross income on energy (Scheier and Kittner, 2022; Drehobl and Ross, 2016). As we show in Table 1 this threshold rests on the principle that energy expenditures should not surpass 20% of housing expenses, which themselves should not exceed 30% of household income (Scheier and Kittner, 2022). However, some researchers advocate for a different approach to calculating energy burden—for example, through the Energy Affordability Gap, which quantifies the gap between 'affordable' home energy bills and 'actual' home energy bills (Fisher, N.d.). Others proposed using a range of energy poverty thresholds. In the study of Colorado energy burden, (Cook and Shah, 2018) classified households as 'energy stressed' (4%-7% burden), 'energy burdened' (7%-10%), and 'energy impoverished' (over 10%). Researchers also use the area median energy burden as a threshold for affordable energy in cross-regional analyses. For example, (Drehobl and Ross, 2016) considered households energy burdened if their expenses exceed the city's median.

3.1.2 Prevalence of Energy Poverty in the U.S.

As (Bednar and Reames, 2020) show, although the U.S. government does not officially recognize energy poverty as a distinct issue—unlike food insecurity, which is formally defined by the United States Department of Agriculture (USDA) (*USDA ERS - Definitions of Food Security*, N.d.)—significant

[4]The strategy initially defined a fuel-poor household as "one which needs to spend more than 10% of its income on all fuel use and to heat its home to an adequate standard of warmth."

Table 1: Example of an Energy Non-Burdened Household vs. a Burdened Household

Criteria	**Household Exceeding 6%**	**Household Not Exceeding 6%**
Annual Income	$50,000	
Max Shelter Costs (30%)	$15,000	
Max Utility Costs (20%)	$3,000	
Actual Utility Costs	$3,500	$2,500
Utility % of Income	7% $(\frac{\$3{,}500}{\$50{,}000} \times 100)$	5% $(\frac{\$2{,}500}{\$50{,}000} \times 100)$
Result	Exceeds (Energy Burdened)	Within (Not Burdened)

policy interventions have been implemented to mitigate it (see Section 3.1.3). This places energy poverty in a paradoxical position: it is simultaneously a *de facto* issue addressed through policy interventions and an issue that remains unrecognized in federal policy.

Still, energy poverty is a federal, state, and local problem, as evidenced by the presence of federally funded energy programs (mainly LIHEAP and WAP), state-led energy initiatives, and county-level and specific energy utilities programs. Researchers in the U.S. have studied the extent of energy burdened households. There is a solid understanding of the experiences of affected households and factors contributing to energy poverty. Some calculations show that if we use the energy burden metric defined as spending more than 6% of household income on energy expenditures, 16% of households experience energy poverty in 2022 (Drehobl, Ross and Ayala, 2020).

Others report that more than 25% (30.6 million) of U.S. households face a high energy burden (> than 6% of income), with approximately 50% (15.9 million) of these suffering from a severe energy burden (> than 10% of income) (Drehobl, Ross and Ayala, 2020). This issue is particularly severe for low-income households, where 67% (25.8 million) encounter a high energy burden and 60% (15.4 million) of these face a severe energy burden. An average residential household varies around 3% of its income on energy bills, while low-income households pay an average of 6% to 8% of their income for energy (Cluett, N.d.; Scheier and Kittner, 2022).

In short, energy poverty is a widespread issue that disproportionately affects low-income households. As energy prices escalate and the impacts of climate change intensify, the number of people struggling to afford basic energy needs is expected to grow (De Cian and Sue Wing, 2019). This trend not only exacerbates social inequalities but also poses severe health and quality of life risks, particularly for vulnerable groups as (Teller-Elsberg et al., 2016; Hernández, Aratani and Jiang, N.d.; Jenkins et al., 2016). Specifically, low-income families, renters, African-American families, and Latino families paid more for utilities per square foot than average households (Drehobl and Ross, 2016). In the regional analysis across American cities of energy burden, metro areas in the Midwest and Southeast had the highest median energy burdens across all groups, with African-American and low-income multifamily households the worst-off in these regions (Drehobl, Ross and Ayala, 2020).

The LIHEAP, as mentioned previously, the primary energy policy intervention to address low-income households estimates that around 33.4 million households were eligible receive LIHEAP benefits in 2020 (*Custom Reports | LIHEAP Performance Management*, N.d.). These households are income-eligible for LIHEAP since their annual income does not exceed a maximum level set by the grantee. This level must be no lower than 110% of the household poverty (*LIHEAP Performance Management Website Glossary*, N.d.). In Table 2, we detail trends in LIHEAP eligibility, showing an increase in eligible households across all poverty levels until 2015, followed by a slight decrease by 2020. Despite this, the percentage of income-eligible households *actually served* remains below 20%.

We also report the geographical and temporal variation in the percentage of income-eligible households served by different types of LIHEAP assistance from 2001 to 2020. The first set of maps (Figure 2) shows the distribution for heating assistance. These maps effectively demonstrate overall underperformance of LIHEAP and the uneven impact and reach of LIHEAP funds across different regions and assistance types.

Table 2: LIHEAP Eligibility and Service Rates

Year	Total Eligible	Eligible <100% Poverty	Eligible >150% Poverty	% Served	Actually Served (M)
2001	29.44M	11.16M	8.71M	N/A	N/A
2005	34.85M	12.78M	11.48M	N/A	N/A
2010	34.37M	14.05M	9.86M	N/A	N/A
2015	35.54M	15.45M	9.09M	17.57%	**6.24**
2020	33.44M	14.04M	9.28M	16.84%	**5.63**

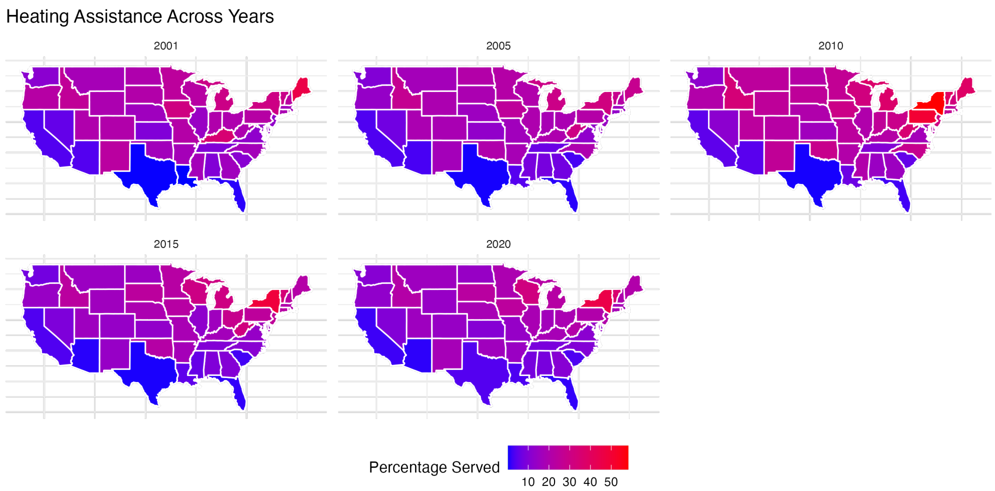

Figure 2: Geographical distribution of heating assistance provided to income-eligible households over two decades.

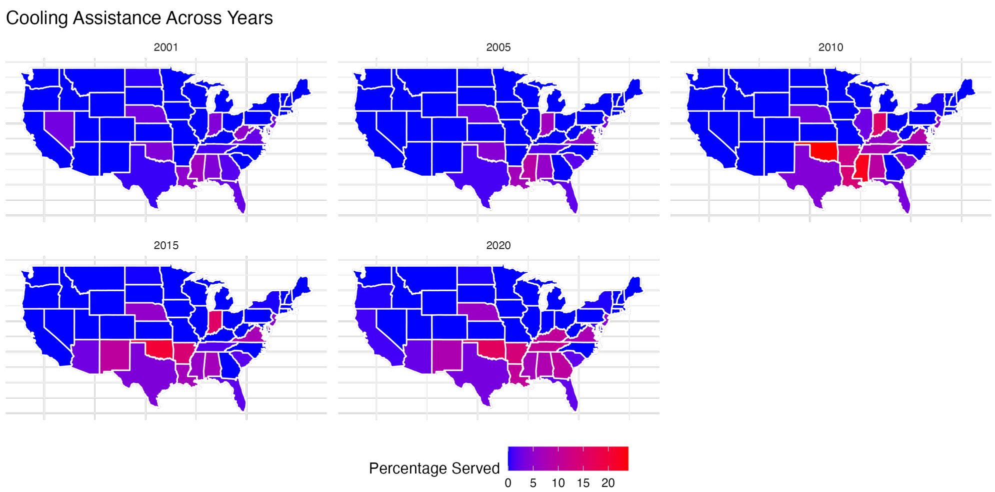

Figure 3: Geographical distribution of cooling assistance provided to income-eligible households over two decades.

3.1.3 Overview of Existing Subsidies in the US

This section presents the current energy subsidies in the US and their effectiveness in addressing energy poverty. There are three primary forms of energy assistance in the U.S. First, the most direct is the provision of subsidies for household energy bills. The majority of funds is channelled to utilities to assist households directly (Drehobl and Ross, 2016). Second, weatherization programs target the actual housing units themselves by addressing the longer-term energy needs of households through measures such as insulation and weatherstripping. Finally, utility energy efficiency programs tend to focus on energy efficiency but vary greatly across states (Brown et al., 2020). For example, in-house rehabilitation programs followed by weatherization programs work in tandem to assist with cases in which weatherization can not yet be carried out. In the US, a federal example of the first type is the Low Income Home Energy Assistance Program (LIHEAP), an example of the second type is the Weatherization Assistance Program (WAP), and an example of the third type at the state level includes the St. Johns Housing Partnership in Florida (Cluett, N.d.).

The primary energy policy in the U.S. LIHEAP, established in 1981 to provide essential support to families struggling with home energy costs, especially during extreme temperature periods(*LIHEAP Fact Sheet*, N.d.). Despite increased funding over the years, LIHEAP continues to fall short of meeting the overall need. More than 10–15 million households face arrearages or potential shut-offs from their electric and natural gas services. As we report in Table 2 in 2020, LIHEAP provided assistance to only about 5.63 million households, while the number of eligible low income households is 14.04 million. LIHEAP offers four types of services: heating assistance, cooling assistance, crisis assistance, and weatherization assistance, each designed to address specific aspects of energy poverty across different times of the year.

3.1.4 Justice component

Historically, LIHEAP performance metrics have not captured demographic data, leaving a gap in understanding the program's impact on various populations. The program focused primarily on poverty levels and estimated income, targeting vulnerable groups identified as older adults (over 60), persons with a disability, or households with young children [5]. There is no data publicly available on how assistance is distributed among different demographics such as gender, renter status, race, and ethnicity. It remains unclear how these groups are specifically affected by LIHEAP benefits [6].

It is puzzling because scholars have consistently shown that African-Americans, along with Latino households and renters, face significantly higher energy burdens compared to the national median (Brown et al., 2020; Hernández and Bird, 2010; Hernández, Aratani and Jiang, N.d.; Hernández, 2016). For instance, African-Americans are more likely to reside in older, energy-inefficient homes with structural deficiencies and outdated appliances, which contribute to higher energy costs and lower living comfort (Lewis, Hernández and Geronimus, 2019). In general, households in communities of color experience energy poverty at rates significantly higher—60% greater—than those in predominantly white communities(Drehobl and Ross, 2016). Such disparities illustrate the dispro-

[5] LIHEAP recently updated its methodology and included new performance metrics such as energy burden, energy security, service restoration and targeting indices (*LIHEAP Performance Management Website Glossary*, N.d.). These measures should reflect the program's effectiveness in reducing energy cost burden on low-income population and show if it is serving the neediest households (*LIHEAP Performance Management Website Glossary*, N.d.).

[6] In response to these data gaps, LIHEAP announced in 2022 that future collection would include demographic metrics. The LIHEAP Household Report will be revised to include the number of assisted households by demographic information. This includes reporting on race, ethnicity, and gender. Initially optional for FY 2023, these measures will become mandatory starting FY 2024. It is unclear when and if this data will be made available to the public.

portionate energy costs burdening low-income households.

Programs like WAP and LIHEAP are designed to alleviate these energy burdens, but they fall short in overall implementation and reach. WAP on average serves about 35,000 homes each year using DOE funds which is approximately 0.089 % of the 39.5 million households that were federally eligible to receive WAP assistance (Rose, 2020). Similarly, LIHEAP, despite its broad scope, served only 16% of eligible households in 2020. These programs often face bureaucratic hurdles, distrust from potential beneficiaries, and stringent eligibility criteria that limit their effectiveness and accessibility (Cluett, N.d.). Still, while detailed impacts of energy assistance programs like LIHEAP across various demographics beyond income levels remains limited, the available evidence shows positive effects. Research from (Murray and Mills, 2014) indicates that participation in LIHEAP improves energy security among low-income households. They estimate that eliminating this support will decrease the number of low-income energy secure households by over 17%.

4 Hypothesis

Our hypotheses are structured around the different effects that pricing schedules can have on various socioeconomic groups preferences. We derive them from our literature review on the state of energy poverty, focusing on who is more likely to be energy burdened and in need of assistance, as well as general political and economic expectations about the distinct effects of energy schedules in 2015 versus 2020. Therefore, we test three hypotheses based on three main groupings to reveal preferences and examine the effects of pricing schedules across income levels (poverty), racial and ethnic backgrounds, and whether a household received energy assistance.

First, higher-income households spend a smaller percentage of their income on energy (Drehobl, Ross and Ayala, 2020). This allows them to more easily shift preferences in response to price changes, so on average, we would expect higher-income households to have stronger preferences for different price schedules compared to lower-income households. We remain agnostic in our Hypothesis 1 about specific preferences for the years 2015-2020 because our focus is to understand the overall preference of higher-income households to varying price schedules first, rather than predicting exact preferences for each specific year. Likewise, if poorer populations were found to have stronger preferences than higher-income households on average, it would contradict our expectations about overall households preferences, as population below poverty level more constrained by their budgets and less able to adapt to changes in energy pricing. This leads us to our first main hypothesis:

Hypothesis 1.
More households above the poverty level will show a greater preference in response to varying pricing schedules compared to households below the poverty level.

Second, energy-burdened populations are disproportionately Black and Latino, who often face higher energy costs relative to their incomes (Drehobl and Ross, 2016). An analysis of four national energy surveys (RECS) found that African-American households consume the most natural gas (Adua and Sharp, 2011). In addition, research shows that natural gas consumption differs by residential location only to the extent that investment in energy efficiency and weather conditions are not taken into consideration. Even after accounting for housing characteristics, investment in energy efficiency, weather conditions, and other critical covariates, African-Americans' higher natural gas consumption persists (Adua and Sharp, 2011). Recent research has found that utility revenues respond asymmetrically to changes in the customer base, with new customers leading to one-to-one revenue increases and customer losses resulting in less than one-to-one decreases (Davis and Hausman, N.d.). Remaining customers make up about half of the lost revenue through increased prices, which has significant equity implications for cities with high poverty rates and large African-American populations, such as parts of the Rust Belt and Appalachia, as well as some rural areas. This indicates that there are underlying factors driving this higher consumption and larger bills that future research needs to further investigate.

Overall, these trends suggest that higher-income households who are better positioned economically will prefer electricity over natural gas under any pricing schedules. At the same time, this would suggest that higher proportion of White households are likely to show a preference for electricity over natural gas, as the benefits of new pricing schedules disproportionately favor wealthier demographics who tend to be White. This leads us to two sub-hypotheses.

Hypothesis 1a.
A higher proportion of households above the poverty level will show a greater preference shift towards electricity over natural gas compared to households below the poverty level.

Hypothesis 1b.
A higher proportion of White households will show a greater preference for decreases in electricity prices over natural gas compared to Black and Latino households.

Hypothesis 2
Fewer households receiving energy subsidies are positively responsive to changes in price schedules, i.e., lower proportion that revealed prefer one over the other, compared to those not receiving subsidies.

Third, previous research has shown that African-American families and Latino families pay more for utilities per square foot than average households. They also have the highest median energy burdens across all groups, with African-American households being the worst-off (Drehobl and Ross, 2016). This leads us to construct the third main hypothesis.

Hypothesis 3
White households are more responsive to changes in price schedules, i.e. more likely to prefer one over the other, given even a small change as compared to Black and Latino households.

5 Application and Data

5.1 RECS Survey

We analyze preferences of households toward different types of energy sources through pricing schedules usign the Residential Energy Consumption Survey (RECS) data from 2015 and 2020. It is a national sample survey administered by the U.S. Energy Information Administration that collects energy-related data for housing units occupied as primary residence and the households that live in them[7].

The 2015 and 2020 RECS study represents the 14th and 15th iterations of the program. The data is collected from nearly 18,500 households in housing units statistically selected to represent the 123.5 million housing units that are occupied as primary residences. This sample is fairly comparable to the number of observations in applications of (Deb et al., 2023). The structure is also similar as they use expenditure and spending surveys, while RECS follows the same approach but also reports consumption in real units (e.g. kWh for electricity). The nature of repeated cross-section of RECS is

[7]The Residential Energy Consumption Survey (RECS) provides the only national data on energy characteristics, usage, and costs for U.S. households. It starts with a survey gathering information on the home's physical attributes and energy usage patterns. Following this, the Energy Information Administration (EIA) contacts the home's energy providers to obtain detailed fuel consumption and cost data. For instance, if a house uses natural gas, the EIA requests the supplier to report both the volume used and the cost. The collected data are then analyzed and estimates of energy consumption for various end uses, including heating, cooling, water heating, and refrigeration are reported for each household separately.

also the same for the data in the paper.

Table 3 describes and compares the overall sample size based on several demographic splits. In 2015, the RECS dataset comprises 5,686 total observations, while the 2020 dataset significantly expands to 18,496 observations. This increase in sample size enhances the robustness and representativeness of the 2020 data.

The "Access to both" column indicates a subsample of the dataset where households had access to both gas and electricity for at least one of the applications, either space heating or water heating. This is a primary subset used in our analysis. In 2015, 1,212 households had access to both, compared to 4,549 in 2020. The "All 4" column represents households that used both gas and electricity for both space and water heating, showing 3 households in 2015 and 29 in 2020. We report this column to highlight the relative rarity of a household that utilizes a wide variety of energy sources for several applications. However, this strict condition is not necessary for us to be able to reconstruct preferences. One combination is more than enough to identify access, or, at the very least, the ability to shift, from one source of energy to another in both applications.

From 2015 to 2020, we see the racial makeup, education levels, poverty and assistance status remain relatively stable. There is a slight rise in respondents with higher education levels that might reflect broader societal trends towards increased educational attainment, which could influence energy consumption patterns and preferences. It is noteworthy that the percentage values for "Full sample" and "Access to both" are very comparable across all splits in all groups. This is a relatively important observation for us, since the subsample "Access to both" ought to be representative of the underlying population if we decide to split it further by demographic characteristics. We see that even though the size is significantly smaller, the fractions of groups in all 4 splits are consistent with the full sample.

Table 4 focuses on space heating by primary equipment and water heating by primary source. It distinguishes between households using only electricity and natural gas (NG), and those using both for heating purposes. We do not provide a full breakdown of all other equipment and sources of energy for the following reasons. Most of the space and water heating is done mostly with a central furnace as a primary equipment, which is often complemented by a secondary portable heater. The former is 279 households in 2015 and 891 households in 2020 in our sample. The latter is the corresponding column, "Both". Note that the combination of "Only NG" and "Both" is over 50% in both years. This also highlights the primary way people substitute natural gas with electricity for heating.

For water heating, the situation is a bit more stratified. Most households either use only electricity or only natural gas. For example, natural gas was the primary source for 57.67% of households using only natural gas and 1.40% of those using both electricity and natural gas. Electricity was the primary source for 37.54% of households using only electricity and a negligible 0.08% of those using both. There is a similar pattern in 2020. This might indicate that the decision for a water heating source is more static and is not made on a month-over-month basis. However, we anticipate that a household has to make such a decision on average every 8 to 12 years [8]. Therefore, there is still substitution based on prices that are simply not captured because of the repeated cross-section nature of the data.

[8] https://worldmetrics.org/average-life-of-water-heater/#sources

	2015			2020		
	Full sample	Access to both	All 4	Full sample	Access to both	All 4
Total obs.	5686	1212	3	18496	4549	29
Split A: Race						
White	4642	965	3	15416	3676	23
	[81.63]	[79.62]	[100]	[83.34]	[80.80]	[79.3]
Black&Latino	680	145	0	1787	508	3
	[11.95]	[11.96]	[0]	[9.66]	[11.16]	[10.3]
Asian	242	74	0	833	248	3
	[4.25]	[6.10]	[0]	[4.50]	[5.45]	[10.3]
Other	122	28	0	460	117	0
	[2.14]	[2.31]	[0]	[2.48]	[2.57]	[0]
Split B: Education						
No degree	405	59	1	773	163	1
	[7.12]	[4.86]	[33.3]	[4.17]	[3.58]	[3.44]
High-school	3239	671	2	9318	6	
	[56.96]	[55.36]	[66.7]	[50.37]	[45.59]	[20.68]
College	1185	261	0	4777	1291	8
	[20.84]	[21.53]	[0]	[25.82]	[28.37]	[27.58]
Graduate	857	221	0	3628	1021	14
	[15.07]	[18.23]	[0]	[19.61]	[22.44]	[48.27]
Split C: Poverty						
Above	4999	1075	2	15935	3948	27
	[87.91]	[88.69]	[66.67]	[86.15]	[86.78]	[93.10]
Below	687	137	1	2561	601	2
	[12.08]	[11.30]	[33.3]	[13.84]	[13.21]	[6.89]
Split D: Assistance						
Recipient	345	88	0	854	221	2
	[6.06]	[7.26]	[0]	[4.61]	[4.85]	[93.10]
Non-recipient	5341	1124	3	17642	4328	27
	[93.93]	[92.73]	[100]	[95.38]	[95.14]	[6.89]

Table 3: We report the number of observations for each group in each split. In brackets, we report the percentage of this group in each dataset considered.

	2015			2020		
	Only electricity	Only NG	Both	Only electricity	Only NG	Both
Space heating: by primary equipment						
Central Furnace		279 [23.01]	469 [38.69]		891 [19.58]	1870 [41.10]
Portable heater	23 [1.89]		3 [0.24]	50 [1.09]		0 [0]
Water heating: by primary source						
Natural gas		699 [57.67]	17 [1.40]		2602 [57.19]	69 [1.51]
Electricity	455 [37.54]		1 [0.08]	1649 [36.24]		31 [0.68]

Table 4: Data on number of observations for each combination of most popular equipment for space heating and most popular sources of fuel for water heating. The number in brackets is the percentage of households in our sub-sample that are in the group.

6 Model and Methods

The methodological approach of this paper can be split into two distinct parts. First, we conduct a nonparametric analysis of the Random Augmented Utility Model to test that our repeated cross-section of consumption data has been generated by a population of rational consumers in a setting with four goods and allowing for unrestricted unobserved heterogeneity. The rationality in this context means we can find a utility function(of any form) that does not imply any contradiction, such as buying more for a higher price. This notion is further expanded upon in the revealed price preference section. The approach was first suggested by (Kitamura and Stoye, 2018) and then improved (Smeulders, Cherchye and De Rock, 2021) and used in a wide variety of contexts individual preferences for things from non-durables to medical insurance coverage plans (Tebaldi, Torgovitsky and Yang, 2023). Even though this step is essential for the price preference analysis to take place, we do not report the results as most of it just confirms that the household's choices are rationalizable.

The second part is establishing bounds on the fraction of households who are revealed to prefer one price schedule over another. This is a direct implementation of a recent work expanding Revealed Preference Theory to include preferences for prices (Deb et al., 2023). The intention is to capture how "well-received" new prices are based on consumer decisions and to conduct some welfare analysis by calculating compensating variation. This is not yet implemented as the analysis has proven to be computationally demanding.

6.1 Random Augmented Utility Model (RAUM)

Let $\mathcal{X}$ represent the set of all choice options x_i, with $\mathcal{X}$ be the space of choice options, and let $u : \mathcal{X} \to \mathbb{R}$ denote a utility function. For simplicity, assume $u(x_i) \neq u(x_j)$ for all $x_i, x_j \in \mathcal{X}, i \neq j$. A choice situation t is characterized by a subset of the discrete choice options, denoted $\mathcal{X}_t \subseteq \mathcal{X}$. Our application has 2 choice situations, and every choice set $\mathcal{X}_t$ contains I_t choice options. A rational individual with a utility function u picks the choice option x that satisfies

$$x = \arg\max_{x_j \in \mathcal{X}_t} u(x_j).$$

Given the nature of the choice sets $\mathcal{X}_t$, a finite number of possible choice profiles are defined over choice situations. Each such profile can be treated as a choice type, indexed by r. Specifically, we encode a choice type r as $a_r = (a_{r,1,1}, \ldots, a_{r,T,I_T})$, with $a_{r,t,i} = 1$ if choice option x_i is chosen in situation t by type r and $a_{r,t,i} = 0$ otherwise. The set of rational choice types $\mathcal{R}$ is the set of all types r for which there exists some utility function u_r such that

$$a_{r,t,i} = 1 \quad \text{if and only if} \quad x_i = \arg\max_{x_j \in \mathcal{X}_t} u_r(x_j).$$

An *random expenditure-augmented utility function* or simply, an *random augmented utility function*, is a function $u : \mathbb{R}_+^{\mathcal{X}} \times \mathbb{R}_- \to \mathbb{R}$, where $u(x, -e)$ is the consumer's utility when she spends e to purchase bundle x. We require that $u(x, -e)$ is strictly increasing in the last argument (in other words, is strictly decreasing in expenditure), which captures the tradeoff the consumer faces between consuming x and consuming other goods (outside the set $\mathcal{X}$).

Let M_R be a probability distribution over all rational choice types, and let μ_r be the probability of a given choice type. We define the sets $\mathcal{R}_{t,i}$ as the subsets of $\mathcal{R}$ such that $r \in \mathcal{R}_{t,i}$ if and only if $a_{r,t,i} = 1$, that is, $\mathcal{R}_{t,i}$ is the set of rational choice types that choose x_i in choice situation t.

Assume a set of observed choice situations for a given population, and let $\pi_{t,i}$ denote the probability that option i is chosen in situation t. Stochastic rationalizability requires there exists a probability distribution M_R such that, summed over all rational choice types r, the probability of choosing option x_i in situation t (given by $\sum_{r\in\mathcal{R}_{t,i}}\mu_r$) equals $\pi_{t,i}$. For the choice probabilities $\pi = (\pi_{1,1},\ldots,\pi_{T,I_T})$ representing the choice probabilities, we thus have the following definition.

Definition: The choice probabilities π are stochastically rationalizable if and only if there exists a distribution M_R over choice types such that

$$\pi_{t,i} = \sum_{r\in\mathcal{R}_{t,i}} \mu_r, \quad \forall t = 1,\ldots,T,\, \forall x_i \in \mathcal{X}_t.$$

6.2 Revealed Price Preference

Since the test for rationalizability involves finding a distribution M_R over different types, it is possible to use this distribution for welfare analysis. To be specific, we can find out the fractions of the population that prefer $p^{t'}$ to p^t.

So consider a data set $\mathcal{D}$ that contains among its observations the prevailing prices $p^{t'}$ and the demand distribution $\pi^{t'}$. To determine the welfare effect of a price change from $p^{t'}$ to p^t, let $\mathbb{P}_{p^t\succeq_p p^{t'}}$ denote the row vector with its length equal to the number of rational types ($|\mathcal{A}|$), such that the jth element is 1 if $p^t \succeq_p p^{t'}$ for the rational type corresponding to column j of A and 0 otherwise.[9] In words, $\mathbb{P}_{p^t\succeq_p p^{t'}}$ enumerates the set of rational types for which p^t is revealed preferred to $p^{t'}$. If $\mathcal{D}$ is rationalizable,

$$\underline{\mathcal{N}}_{p^t\succeq_p p^{t'}} := \min_M \mathbb{P}_{p^t\succeq_p p^{t'}} M, \quad \text{subject to } AM = \pi, \tag{1}$$

is the lower bound on the proportion of consumers who are revealed better off at prices p^t compared to $p^{t'}$, while the upper bound is

$$\overline{\mathcal{N}}_{p^t\succeq_p p^{t'}} := \max_M \mathbb{P}_{p^t\succeq_p p^{t'}} M, \quad \text{subject to } AM = \pi. \tag{2}$$

Since (1) and (2) are both linear programs (which have solutions if, and only if, $\mathcal{D}$ is rationalizable), they are implementable in practice. Suppose that the solutions are $\underline{M}$ and $\overline{M}$ respectively; then for any $\beta \in [0,1]$, $\beta\underline{M} + (1-\beta)\overline{M}$ is also a solution to $AM = \pi$ and, in this case, the proportion of consumers who are revealed better off at p^t compared to $p^{t'}$ is exactly $\beta\underline{\mathcal{N}}_{p^t\succeq_p p^{t'}} + (1-\beta)\overline{\mathcal{N}}_{p^t\succeq_p p^{t'}}$. In other words, the proportion of consumers who are revealed better off can take any value in the interval $[\underline{\mathcal{N}}_{p^t\succeq_p p^{t'}}, \overline{\mathcal{N}}_{p^t\succeq_p p^{t'}}]$. However, if M_R is uniquely identified, the interval is point identified. This is the case for our application, so the values reported in our results are all point estimates.

7 Results

We apply our methods to the 2015 and 2020 Residential Energy Consumption Survey rounds. The estimates for RAUM can be thought of as conducting a revealed preference analysis for a representative consumer. To facilitate our analysis, we constrain the selection to only households that had verifiable access to both sources of energy for both water and space heating. The data is further broken down by demographic characteristics, such as race, education level, poverty status, and energy assistance status. While household budgets have a tendency to move outward over time, there is a substantial overlap of budgets at median expenditure. To account for endogenous expenditure, we

[9] $\mathbb{P}_{p^t\succeq_p p^{t'}}$ enumerates the set of rational types for which p^t is revealed preferred to $p^{t'}$.

follow (Kitamura and Stoye, 2018), using total household income and number of members as the instruments. For each group, we reconstruct a unique and uniform schedule of prices faced each year and assume that any variation in individual pricing is captured by prior adjustment of expenditure.

The primary comparison here is between price schedules in 2015 and 2020 that encompass 4 composite goods: electricity for space heating and water heating, and natural gas for heating and water heating. The corresponding prices are $p^E_S, p^E_W, p^G_S, p^G_W$. The results for each demographic are presented in the set of two tables. The first set of Tables (5, 7, 9, 11) in each section provides an estimate of the fraction of households in each group that are revealed as better off at one price schedule over the other. It is not necessarily the case that these fractions should sum up to 1. A portion of households might be indifferent between the options. Thus, the strict preference doesn't capture this residual number, and the two reported fractions do not constitute the whole population. The method allows us to estimate the bounds of each fraction, while the tables only report point estimates and confidence intervals. The second set of Tables (6, 8, 10, 12) outlines the percentage change in each component of the price schedule, informing the analysis of what components of the price schedule might drive differences observed in the results from the first set of Tables.

Notably, we do not make any claims on underlying reasons behind the revealed preferences for one price schedule over the other. It might be driven by socioeconomic factors, historical realities, and a myriad of other reasons, from the availability of better household appliances to the habitual desire to stick to a particular energy source. All breakdowns serve as a way to analyze the decisions of people with different distributions of preferences, and each category just serves as a convenient proxy for capturing subsets of populations with relatively similar preferences. A post hoc rationalization of why the breakdowns help is the relative tightness of confidence intervals for the estimated fractions. If the population splits did not reflect groups with similar preferences, the confidence intervals would either diverge or the dataset itself would not be rationalizable.

7.1 Race

The first population breakdown of interest is racial background. Table 6 presents the results for households that in the RECS indicated all their members to be of a single race, or a mixed composition. The fraction of white households that are revealed prefer price schedule p^{20} to p^{15} is around 75%, while the same metric is only 60% among Black & Latino group. Both numbers are above the majority, which indicates that the movement from one schedule to another is overall preferred by population. However, the notable difference of 15% between groups signals that more households with white racial backgrounds benefited from the change than black ones. Table 6 can shed some light on why that might be the case.

In general, price schedules moved in a similar manner for both groups. The prices for electricity fell while natural gas became more expensive. The extent of these changes, though, was different. From 2015 to 2020, natural gas has become 16% more expensive for households with a white background, which is over 10% greater than the corresponding change in the other group. On the other hand, households with Black & Latino backgrounds experienced a 7% decrease in electricity pricing, a 2% lower than what was observed for their counterpart. With both changes combined, it might seem that the prices p^{20} are undeniably better for Black & Latino households as they saw smaller increases and larger decreases. Following this logic, one could conclude that the fraction of households who prefer the more recent price schedule should also be greater among Black & Latino and not White households. But this would directly contradict the estimates in Table 3.

One logical explanation, which we think is probably the case, is that there is a stronger preference for natural gas as an energy source among Black & Latino households. Even though the increase p^G_S and p^G_W is not as pronounced for them as for White households. If a strong aversion to increases in the prices of gas is present only among minority groups, then even a small increase would be enough to overshadow any decreases in electricity prices and drive down the fraction of households who prefer a newer price schedule over the older one. This has an obvious implication for the construction of subsidies if such subsidies are targeted at Black & Latino households. A policy that aims to promote the consumption of relatively greener energy (e.g., electricity price assistance) and disincentives the use of fossil fuels (e.g., reductions in natural gas price assistance) might leave the households worse off, even if the former is significantly greater than the latter.

	Fraction of households [Confidence interval]			
Comparison	White	Black&Latino	Asian	Mixed
$p^{2020} \succ^* p^{2015}$	0.7546	0.6011	.	1
	[0.7429, 0.7663]	[0.5577, 0.6446]	.	[1, 1]
$p^{2015} \succ^* p^{2020}$	0.2454	0.3034	.	0
	[0.2356, 0.2552]	[0.2276, 0.3793]	.	[0, 0]

Table 5: Fraction of households that prefer one price schedule over the other split by race

Breakdown	p_S^E	p_W^E	p_S^G	p_W^G
White	-5.86%	-5.86%	16.42%	16.42%
Black & Latino	-7.81%	-7.81%	5.26%	5.26%
Asian	-11.91%	-11.90%	12.05%	12.05%
Mixed	-7.51%	-7.51%	-29.36%	-29.36%

Table 6: Change in prices from 2015 to 2020

7.2 Poverty

The next population breakdown of interest is poverty status. Table 7 presents the results for households whose income per member is below and above 100% of the federal poverty threshold. The fraction of non-poor households that are revealed prefer price schedule p^{20} to p^{15} is around 86%. Notice that there is no estimate for households in poverty. The reason why is straightforward. In our data, the change in price schedule is a strict improvement for households across both sources of energy. Under the new, lower prices p^{20}, the fraction should be just 1. However, this is not the case per se since some portions of the data are not rationalizable. We suspect that the reason for that is the imperfections in how we incorporate income data that RECS provides in the form of several ranges. It makes the expenditure adjustment imperfect and introduces flaws during the construction of the uniform price schedule for a relatively small number (around 11%) of households in poverty.

7.3 Education

The results for the educational breakdown are presented in Tables 9 and 10. Note that a similar problem as in the poverty section is present for households with the highest level of education lower than high school diplomas. The small number of such survey participants (less than 60 in both years) makes the constructed price schedules unreliable and data non-rationalizable. Fortunately,

	Fraction of households [Confidence interval]	
Comparison	Below	Above
$p^{2020} \succ^* p^{2015}$	1	0.8692
	[1, 1]	[0.8490, 0.8853]
$p^{2015} \succ^* p^{2020}$	0	0.1308
	[0, 0]	[0.1129, 0.1451]

Table 7: Fraction of households that prefer one price schedule over the other split by poverty threshold.

Table 8: Change in prices from 2015 to 2020

Breakdown	p_S^E	p_W^E	p_S^G	p_W^G
Below	-3.95%	-3.95%	-28.69%	-28.69%
Above	2.35%	2.35%	-14.97%	-14.97%

there are no such problems for other groups. The fraction of high school-educated households that are revealed prefer price schedule p^{20} to p^{15} is around 75%, while the same metric is only 200% among households where a member attained an undergraduate degree. Both numbers are above the majority, indicating that the movement from one schedule to another is preferred for these two groups.

This result is somewhat consistent if you consider the following. In general, price schedules moved in a similar manner for both groups. The prices for electricity fell while natural gas became more expensive. The fact that we estimate that almost a quarter of HS households prefer the old price schedule indicates, again, that there is a considerable portion of the population with a strong preference for natural gas as a source of energy. This group, however, is only imperfectly captured by the breakdown based on education as we see a higher fraction in HS than in UG that prefers p^{20}.

	Fraction of households [Confidence interval]			
Comparison	No	HS	UG	G
$p^{2020} \succ^* p^{2015}$	1	0.7506	0.6590	.
	[1, 1]	[0.7371, 0.7642]	[0.6054, 0.7126]	.
$p^{2015} \succ^* p^{2020}$	0	0.2494	0.1464	.
	[0, 0]	[0.2377, 0.2610]	[0.1278, 0.1650]	.

Table 9: Fraction of households that prefer one price schedule over the other split by highest educational level completed.

7.4 Assistance

The results for the last breakdown, assistance received, are presented in Tables 11 and 12. For the group who didn't receive the assistance, both the fraction of households and price changes are consistent with previous breakdowns. In contrast, only the directionality in price changes is consistent

Table 10: Change in prices from 2015 to 2020

Breakdown	p_S^E	p_W^E	p_S^G	p_W^G
No	-4.18%	-4.18%	-4.62%	-4.62%
HS	-4.15%	-4.15%	18.72%	18.72%
UG	-10.79%	-10.79%	14.23%	14.23%
G	-9.74%	-9.74%	5.12%	5.12%

for the people who received assistance; even the changes themselves are of smaller order than previously seen. This might indicate that federal assistance with energy needs acts in such a way that it stabilizes the exogenous parts of prices that we obtain during expenditure adjustment. This complicates the analysis quite a bit since the primary source of variation for uncovering preferences is the changes in price. When those changes are only small percentage movement (and consequently small absolute values), the model does not rationalize any variation in consumption. Since we observe both, changes in consumption and almost no change in price, the approach fails to create consistent bounds on the fractions in population. We plan to address it in further iterations of the analysis, primarily by integrating LIHEAP data into how we adjust the expenditure in both groups.

	Fraction of households [Confidence interval]	
Comparison	Received	Didn't
$p^{2020} \succ^* p^{2015}$	.	0.7546
	.	[0.7445, 0.7648]
$p^{2015} \succ^* p^{2020}$	.	0.2454
	.	[0.2368, 0.2540]

Table 11: Fraction of households that prefer one price schedule over the other split by assistance receipt.

Table 12: Change in prices from 2015 to 2020

Breakdown	p_S^E	p_W^E	p_S^G	p_W^G
Received	-3.43%	-3.43%	1.99%	1.99%
Didn't	-6.84%	-6.84%	13.69%	13.69%

8 Discussion

Our study reveals significant insights into how household energy consumption preferences are shaped by different pricing schedules for electricity and natural gas. By analyzing data from the 2015 and 2020 Residential Energy Consumption Surveys (RECS), we have identified a general preference for the 2020 pricing schedule across most households. However, this preference is not uniformly distributed across different demographic groups. Wealthier households and white households show a stronger preference for the 2020 prices, while energy-burdened groups, particularly Black and Latino households, exhibit less pronounced preferences. These findings suggest that while the 2020 pricing adjustments were broadly favorable, they did not adequately address the specific needs of more financially constrained households.

The differential impacts observed among various demographic groups highlight the importance of considering equity in energy pricing policies. For instance, Black and Latino households, which have historically faced higher energy burdens, show a less pronounced preference for the 2020 pricing schedule. This suggests that the increases in natural gas prices from 2015 to 2020 disproportionately negatively impacted these groups, even though they also benefited from reduced electricity prices. These insights underscore the need for more nuanced energy pricing policies that consider different demographic groups' distinct consumption patterns and economic constraints to promote energy justice.

Next steps. Moving forward, welfare analysis will be a critical component in understanding the broader implications of energy pricing changes. By estimating compensating variation, we plan to quantify the monetary value of welfare changes induced by different pricing schedules. This analysis will allow us to determine how much households would need to be compensated to maintain their utility levels under different price scenarios. Such an approach will provide a transparent way to evaluate the effectiveness of current and proposed subsidy programs, ensuring that they are designed to maximize welfare improvements, particularly for the most vulnerable populations.

Specifically, we plan to conduct a welfare analysis of federal energy assistance programs LIHEAP and WAP. These programs play a crucial role in mitigating energy poverty, but their effectiveness can vary significantly across different regions and demographic groups. By incorporating data on subsidy receipt and other forms of assistance, we can better understand how these programs interact with energy pricing schedules and identify opportunities for policy improvements. Ultimately, our goal is to inform policymakers on how to design equitable and effective energy pricing and subsidy policies that ensure all households have access to affordable and reliable energy.

Appendix

9 Abbreviations

- LIHEAP: Low Income Home Energy Assistance Program
- RECS: Residential Energy Consumption Survey
- EIA: Energy Information Administration
- RUM: Random Utility Model
- RAUM: Random Augmented Utility Modele
- WAP: Weatherization Assistance Program
- Btu: British thermal unit

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