# How Do Residential Greenhouse Gas Mitigation Technologies Affect Electricity Prices and Consumer Welfare?

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# Abstract

Many jurisdictions encourage households to adopt technologies that reduce greenhouse gas emissions and energy consumption, but there is little evidence on how these technologies affect the welfare of nonadopting households. We show that, in theory, adopting climate-friendly technologies that affect aggregate electricity demand, such as rooftop solar photovoltaics or electric vehicles, can increase or decrease average retail electricity prices in the short run; if the variable cost curve for electricity generation is sufficiently flat, higher demand reduces prices (and vice versa). Analysis of US residential electricity price and consumption data, as well as simulations of a computational electricity generation model, suggests that this variable cost condition holds. Adopting technologies that reduce consumption raises average retail prices, harming nonadopters; adopting technologies that increase electricity demand reduces average electricity prices, benefiting nonadopters. Using household survey data, we find that adopting rooftop solar disproportionately harms low-income nonadopting households, whereas adopting electric vehicles disproportionately benefits them. This progressivity roughly offsets the regressivity of the electric vehicle subsidy transfers.

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# 1. Introduction

Encouraging households to reduce greenhouse gas (GHG) emissions is politically popular and widespread globally. Governments at many levels subsidize electric vehicles (EVs), rooftop solar photovoltaics, and weatherizing residential homes. Other policies aiming to reduce residential GHG emissions are also common, such as efficiency and appliance standards for new home construction.

A deepening literature evaluates the environmental benefits of the policies as well as takeup and direct welfare effects on subsidy recipients (e.g., Bento et al. 2009, Borenstein 2017, Bruegge et al. 2019, Coyne and Globus-Harris 2024, Davis and Knittel 2019, Feger et al. 2022, Glaeser et al. 2023, and Williams et al. 2015). For example, Springel (2021), Li et al. (2017), and Xing et al. (2021) evaluate subsidies for EVs and public charging stations in Norway and the United States; and Hughes and Podolefsky (2015), Pless and van Benthem (2019), and Dorsey (forthcoming) analyze rooftop solar subsidies. These subsidies account for much of the adoption of EVs and solar panels to date, although purchase subsidies are sometimes cost-ineffective and high-income consumers tend to capture most of the benefits (Borenstein and Davis 2025).

A common feature of many household GHG policies is that they affect electricity consumption. Some policies, such as subsidizing energy efficiency or rooftop solar, reduce the amount of electricity households purchase from retailers, while others, such as subsidizing EVs or heat pumps, increase electricity demand. By affecting demand, these policies indirectly affect electricity prices of all households, even those who do not adopt the technologies; we refer to such households as nonadopters. Because nonadopters usually account for at least 90 percent of all households, their combined welfare changes may be substantial. Notwithstanding the extensive literature on these policies, for the most part, policy evaluation has focused on takeup and welfare effects for adopters or considered optimal subsidy design, usually focusing on a single technology and without considering how adoption has already affected equilibrium prices and the welfare of nonadopters.

This paper evaluates, both theoretically and empirically, the effects of such GHG-reducing technology adoption on average residential electricity prices and the implications of those price changes for the private welfare of nonadopters. Producing electricity requires payment of sunk costs, such as building transmission infrastructure, and variable costs of fueling electricity generators. In the long run, sunk costs may adjust to aggregate demand—for example, population growth could cause firms to build new electricity generators and transmission capacity. Our theoretical analysis considers a time horizon over which sunk costs have already been paid, and variable costs depend on electricity demand—roughly three years. In equilibrium, technology adoption that raises electricity demand causes average electricity prices to decline if the average variable cost curve is sufficiently flat; or, equivalently, if marginal costs are less than average costs. In other words, adoption of EVs or other technologies that increase electricity demand (such as heat pumps) may reduce electricity prices over the time horizon in which sunk costs have been paid. By extension, if the utility must upgrade the distribution network to accommodate the technology adoption—for example, installing higher-capacity transformers or feeders that support EV charging—adoption that increases demand reduces prices if the variable cost curve is sufficiently flat and the upgrade costs are sufficiently small.

Thus, it's an empirical question about how technology adoption affects retail electricity prices, and we take two approaches to estimate this effect. First, we assume that technology adoption affects retail prices via aggregate annual demand—that is, independently of how adoption affects seasonal or diurnal demand patterns. Under this assumption, we use data on retail sales and consumption by retail electricity suppliers from 1990 to 2022 to estimate the elasticity of the average residential retail price to total residential sales.

Because prices and quantities are determined simultaneously, ordinary least squares (OLS) would yield biased estimates. We instrument for sales using demand shifters to identify the effect of demand-driven demand changes on average prices. Higher consumption reduces prices, with an average elasticity of price with respect to sales equal to about –0.4. The negative elasticity is consistent with a relatively flat average variable cost curve.[1] The magnitude is stable across specifications, including aggregating to two- or three-year time periods to allow for delayed price responses. However, including demand lags indicates that the magnitude diminishes over time since the demand change, which may reflect lags in regulatory price adjustments to capital expenditures.

The second employs an updated version of the Linn and McCormack (2019) model of electricity generation to simulate the effects of a hypothetical demand change on generation and equilibrium prices. In the model, each firm owns a single generator and maximizes profits taking as exogenous aggregate demand, fossil fuel prices, and other firms' decisions. We simulate changes in electricity demand calibrated to EV or solar panel adoption. Compared to the econometrics approach, using the model requires assumptions about market competition and generator costs, but it allows us to isolate the effects of time-varying demand changes on prices without concern for confounding factors.

Similarly to the retail sales results, the simulations indicate that higher electricity consumption reduces average prices. The simulations yield similar estimated price elasticities to the utility-level analysis, of about –0.4. The elasticity is similar whether we model uniform or time-varying demand changes based on EV charging or solar generation profiles, supporting the assumption motivating the sales analysis that adoption affects prices via aggregate demand.

Finally, we use household-level data from the 2020 Residential Energy Consumption Survey (RECS) to quantify the implications for nonadopters of the average price changes caused by adopting solar panels or EVs. We estimate average electricity expenditure changes across households as well as expenditure changes by income

1 Borenstein and Bushnell (2022) find that electricity rates exceed marginal costs. Since rates equal average costs in the long run, their finding indicates that average costs exceed marginal costs, which is consistent with our negative estimate.

group. For an individual household, expenditure changes depend on whether the retailer adjusts fixed charges or variable rates (that is, the rate at which the monthly bill increases with total monthly consumption). For this reason, we allow for the possibility that retailers adjust fixed charges or variable rates in response to the demand change.

We consider four scenarios that vary across two dimensions: (1) whether technology adoption increases or decreases aggregate electricity demand; and (2) whether retailers adjust fixed charges or variable rates. In these calculations, we allow for the possibility that adopting solar panels or EVs requires the electric utilities to make investments in the transmission or distribution network, using estimates of investment costs from Horowitz et al. (2018) and Cutter et al. (2021).

Adopting rooftop solar or other technologies that reduce electricity demand raises average prices. Because low-income households spend a larger share of their income on electricity than do high-income households, these price increases disproportionately harm low-income nonadopters. In contrast, adopting EVs or other technologies that raise demand causes electricity prices to decrease, reducing the income share of electricity expenditure more for low-income nonadopters than for high-income nonadopters. The conclusions are the same whether we consider changes in fixed charges or variable rates.

The results also have significant energy equity implications. Higher-income households are more likely to benefit directly from GHG policies aimed at homeowners or adopters of rooftop solar or EVs. For those policies that reduce aggregate consumption, the resulting electricity price increases make the policies even more regressive than if one only considered the direct private welfare changes for adopters. In contrast, for polices that increase aggregate consumption, the resulting price changes reduce these policies' regressivity. In the case of EV adoption, state and federal subsidies are far less regressive than would appear based on analyzing uptake of the subsidies. High-income households are more likely than low-income households to claim state and federal EV purchase subsidies, but for the most part, the combined expenditure changes—including subsidy payments and changes in electricity bills—vary little across income groups.

This paper complements and builds on several strands of literature. First, Reguant (2019) and Greenstone and Nath (2021), among others, have estimated the effects of renewable electricity policies on retail electricity prices and emissions using econometric and numerical modeling. Our work uses both econometrics and numerical modeling and compares the effects of rooftop solar and EV adoption on nonadopting households.[2]

2 More specifically, Reguant (2019) considers the effects of renewables policies on prices across sectors, rather than households. Greenstone and Nath (forthcoming) use state-level policy and electricity price variation and include both residential and nonresidential renewables investments, whereas we focus on residential solar.

Second, the literature on incomplete regulation considers policies that affect a subset of producers or products. For example, many environmental regulations are vintage differentiated, in that they apply different standards to new and old products or to new and old producers. Such incomplete regulation can affect equilibrium prices of products sold by unregulated producers or prices of closely related goods. For example, Jacobsen (2013) shows that regulating fuel economy of new passenger vehicles affects prices of used vehicles, thereby affecting welfare of nonadopters (i.e., consumers who do not buy the regulated new vehicles). Imposing stricter emissions requirements for new than for old electricity generators delays retirements of older generators and raises electricity prices, and it also reduces efficiency and increases emissions (Bushnell and Wolfram 2012). Houde (2022) shows that labeling certain household appliances as energy efficient affects prices and quality of unlabeled but otherwise similar products. Related to this literature, we find that policies affecting certain products (for example, EVs and solar panels) affect prices of related products (that is, electricity) and welfare of nonadopters.

# 2. Data

This section describes the data used for the three analyses reported in this paper: (1) estimating the effect of electricity consumption on electric utilities' average prices; (2) simulating generator utilization changes caused by an increase in electricity demand; and (3) computing residential household bill changes caused by GHG technology adoption that affects aggregate electricity demand.

## 2.1. Variables Used for Utility-level Analysis

To estimate the effect of electricity consumption on average prices, we combine utility-level data on consumption and prices with other demand and supply-side data. For the period 1990–2022, we obtain the Energy Information Administration (EIA) Form EIA-861 (the Annual Electric Power Industry Report), which is a national census of electric utilities and electricity power marketers. Because some utilities operate in multiple states, the unit of observation is the utility-state-year. For each observation, we obtain revenue (nominal dollars), electricity sales (kilowatt hours), and the number of consumers. For many utilities, revenue, sales, and customer counts are available separately for residential, commercial, and industrial consumers. The data also include ownership type (private or public) and service type (delivery, bundled, or energy). Delivery service utilities oversee transmission and distribution infrastructure, whereas energy service utilities focus on the generation or procurement of electricity. Bundled utilities perform both delivery and energy services. The sample excludes delivery service utilities.

We use temperature data from the National Centers for Environmental Information. The National Centers for Environmental Information data provide monthly average temperatures by state, which are area-weighted averages of temperatures for five-kilometer-square grids (which themselves are interpolated from station-level data). Heating and cooling degree days are measured relative to a baseline of 65 degrees Fahrenheit.

We combine utility-level data with demand and supply-side data from other sources. We construct a proxy for industrial demand based on county-level employment and industry-level electricity consumption. The employment data are from the Quarterly Census of Employment and Wages, from which we obtain employment counts by industry, county, and year.[3] From the Manufacturing Energy Consumption Survey, we obtain the net electricity demand by industry in 1990 and 1998.

We assemble fuel prices from the EIA Form 423/923 from 1990 to 2022. For electricity generation plants that burn fossil fuels (coal, natural gas, or oil), the data contain fuel expenditure and consumption (measured in million British thermal units, mmBtus) by plant, month, and fuel type. For each fuel type, we compute the average price as the ratio of expenditure to consumption by state and year. EIA does not release complete data for merchant generators (that is, generators that are not subject to price regulation), and we construct average prices using only plants with complete data. For states without any complete data, we interpolate prices using average prices of neighboring states. The average fuel price is the consumption-weighted price of the individual fuels.

We merge the temperature, industrial electricity consumption, and fuel price data with the EIA 861 data by state and year. Table 1 provides summary statistics of the key variables in the econometric analysis. All values are in 2022 real dollars (CPI-adjusted). The weighted natural gas price is $1.27/MMBtu, which equals the percentage of gas in total generation (14 percent) multiplied by the average price of $4.35/MMBtu. Figure 1 shows total annual residential sales and the average residential electricity price for 1990–2022. Average prices increased gradually between 1990 and the early 2000s, after which prices increased more rapidly. Residential sales grew steadily through around 2010 before leveling off.

Figure 2 plots the estimated density functions of average prices by interconnection, using the full 1990–2022 sample. Typical prices are fairly similar to one another across the three interconnections. The western interconnection contains substantially more price variation than the other interconnections.

Figure 3 shows estimated density functions of log residential sales and log industrial sales by interconnection. The residential sales distributions are similar to one another, but the industrial sales distribution for the Electric Reliability Council of Texas (ERCOT) is considerably wider than that of the other two interconnections.

Figure 4 illustrates the variation of heating and cooling degree days by interconnection. ERCOT has fewer heating degree days than the other regions but more cooling degree days, which underscores the importance of allowing the two temperature variables to affect residential electricity demand independently of one another.

3 Industries are defined at the two-digit Standard Industrial Classification code for 1990–1997 and at the four-digit North American Industrial Classification System code for 1998–2022. We match the Quarterly Census of Employment and Wage data to the energy consumption data by the corresponding industry codes.

## 2.2. Generator Operation and Fuel Prices

The computational model from Linn and McCormack (2019) relies primarily on the same fuel price data as described in Section 2.1, along with hourly generation and fuel consumption for 2001–2022. The hourly data are from the EPA Continuous Emissions Monitoring System, which includes all fossil fuel-fired generation units with generation capacity of at least 25 megawatts.

Figure 5 shows fossil fuel generation by interconnection (Panel A) and average coal and natural gas prices (Panel B). Note that the ERCOT and western generation levels are plotted on the right axis, and that generation in the East is about six times higher than in the other interconnections. Fossil generation shows similar patterns in the three interconnections, increasing steadily until 2008, before leveling off or declining. The 2008–2009 economic recession and shift toward wind and solar generation explain much of those changes (Borenstein 2012, Cullen 2013, Fell and Kaffine 2018 and Johnsen et al. 2019).

Panel B shows that coal prices were relatively stable, whereas natural gas prices increased until 2008, and then they dropped substantially before increasing again at the very end of the data period. Increasing production from shale formations explains much of the post-2008 price decline for natural gas.

Because the theoretical analysis in the next section highlights the importance of the steepness of the average variable cost curve in determining how electricity demand affects retail prices, Figure 6 plots average variable cost curves for each interconnection in 2008 and 2016. The curves are constructed by creating short-run marginal cost curves for each interconnection and year. As an approximation, if generators in each interconnection operate in a competitive market—and there are no transmission constraints or startup or ramping costs—the short-run marginal cost curve is the horizontal sum of generation capacity that could be produced at or below the cost indicated on the vertical axis of the figure.[4] We construct the average variable cost curves by integrating under the marginal cost curves and dividing by cumulative generation capacity, plotting the results in Figure 6.

In 2008, coal-fired generation units usually had lower marginal costs than natural gas-fired units, and the flat portion of the 2008 curves on the left side comprises primarily coal-fired units. Once generation on the horizontal axis exceeds the total coal-fired capacity, the curves become steeper, which reflects the higher costs of natural gas-

4 In the computational model, the shape of the short-run supply curve varies hourly based on peak daily generation, outages, fuel prices, and other factors. It is simpler to plot the short-run supply curves in Figure 6, which vary only with fuel prices. Notwithstanding the simplifying assumptions, Figure 6 conveys the intuition behind the results from the computational model reported in Section 4.

fired generation. In 2016, when natural gas prices were lower (as Figure 5 shows), the natural gas-fired portions of the average variable cost curves are substantially flatter than in 2008.[5]

## 2.3. Household Electricity Consumption

To simulate retail price and welfare changes caused by hypothetical policy-induced demand changes, we use data from the 2020 RECS. The dataset includes 18,496 households and provides weights for constructing a nationally representative sample. We exclude the 15 households reporting negative annual electricity bills. The RECS data assign each household to an income category, and we use the 2020 American Community Survey data to impute the median income for each group.

Table 2 provides summary statistics for the RECS data. Each cell shows the mean of the variable indicated in the column heading for the income group indicated in the row heading. The income groups are constructed to have similar counts of households across the United States. Electricity consumption and expenditure increase steadily with income, although the share of expenditure in income decreases with income. On average, households in the highest income group are about nine times more likely to have rooftop solar or EVs than households in the lowest income group. Higher-income households have lower cooling degree days than lower-income households, indicating that higher-income households are relatively likely to reside in locations with mild summers. Heating degree days do not vary systematically with household income.

# 3. Estimating the Effect of Electricity Consumption on Average Retail Prices

This section presents the econometric estimates of the effect of demand on electricity prices, which are used to simulate the effects of technology adoption on electricity bills of nonadopters in Section 5. To contextualize the econometric estimation of the effects of electricity consumption on average prices, this section begins with a theoretical framework that illustrates how the slope of the average variable cost curve determines whether higher electricity consumption leads to an increase or decrease in average retail prices. We describe the strategy for estimating the effect of electricity consumption on average prices and present the estimation results.

5 Between 2008 and 2016, a considerable share of coal-fired generators retired, particularly in the East. These retirements contribute to the steepening of the average variable cost curves between those years, which slightly offsets the effects of the lower natural gas prices in Figure 6. Also note that the lower price in 2016 causes some gas-fired generators to have lower costs than some coal-fired generators, which further flattens the curves.

## 3.1. Theoretical Framework

We consider a vertically integrated utility that makes capital investments in generation equipment and transmission and distribution equipment, and supplies electricity to residential households. The utility is subject to rate-of-return regulation, and the model contains three time periods: (1) the utility reports fixed costs and electricity consumption; (2) the regulator determines a price to ensure the utility earns zero economic profits after incorporating opportunity costs; and (3) households consume the amount of electricity the utility reported in the first period and pay their electricity bills given the price. More specifically, the utility has fixed costs *F* and average variable costs *V*, where variable costs include the costs of operating its generators to supply electricity to consumers. Residential demand is *Q*, and the zero-profits condition implies that the average retail price equals average fixed costs plus average variable costs:

$$P = \frac{F}{Q} + V,$$

where *P* is the average price and is equal to the total residential expenditure (including fixed and variable charges), divided by *Q*.[6]

Next, we conduct a comparative statics analysis to derive a condition under which an increase *Q* causes the average price, *P*, to increase. Suppose that consumption is *Q'*, rather than *Q*, where *Q' > Q*. For the moment, we assume that the utility does not have to incur additional fixed costs to meet the higher demand, so that *F'=F*. The higher demand causes the average retail price to increase to *P'*. We define *dP* as *(P' - P)* and similarly for *dV*, which is the change in average variable costs across the two situations. Zero profits imply that the following condition holds:

$$dP = \frac{F}{Q'} - \frac{F}{Q} + dV. \qquad (1)$$

The sum of the first two terms on the right side is the change in average fixed costs, which is negative because the higher quantity reduces average fixed costs. The third term is positive, since variable costs increase when the utility raises generation to meet the higher demand. Consequently, the price change is positive if the change in variable costs exceeds the magnitude of the change in average fixed costs.

Rearranging equation (1) shows that the price change depends on the percent change in quantity and the change in variable costs:

$$dP = -(P - V)\frac{dQ}{Q} + dV \qquad (2)$$

6 The model includes the assumption that the regulator sets a linear price and no fixed charge. In practice, the regulator may set nonlinear prices, such as two-part tariffs or increasing block pricing. The econometric estimation relaxes the assumption of linear pricing.

Equation (2) implies that the price change is positive if the following condition holds:

$$\frac{dV}{V} > \frac{(P-V)}{V}\frac{dQ}{Q'}. \qquad (3)$$

Expression (3) means that the price increases if the percent change of average variable costs exceeds the markup multiplied by the percent quantity change. Thus, the higher quantity causes the price to increase if the average variable cost curve is sufficiently steep.[7] Or, equivalently, the higher quantity reduces the average price if marginal costs are below average costs.[8]

We discuss the implications of three assumptions made so far. First, we derived expression (3) for a rate-of-return regulated utility. An analogous situation exists for a competitive retail electricity market in which firms purchase electricity in a wholesale electricity market and sell electricity to consumers. In this case, if firms make entry decisions after demand is realized, free entry and exit guarantees that price equals average costs, and an expression similar to (3) would hold for each firm. To the extent that firms have to make entry and exit decisions prior to observing demand, average price is more likely to be positively correlated with demand.

Second, expression (3) holds under the assumption that the higher consumption does not affect fixed costs. If the consumption increase is sufficiently large, the utility may incur additional fixed costs to increase transmission capacity or upgrade the distribution network. For example, if EV charging is spatially and temporally clustered (Bailey et al. 2024), even a small consumption increase may cause the utility to invest in the distribution network to handle the localized power demand. In that case, the higher consumption would be more likely to increase the average price than expression (3) implies—that is, the larger the increase in fixed costs, the less steep the average variable cost curve must be for the average price to increase.

Finally, we note that we have focused on residential pricing and excluded pricing for the industrial and commercial sectors, which is valid under the assumption that prices are determined such that price equals average costs for each customer class. We can partially relax this assumption by controlling for industrial consumption in the statistical analysis.

7 The markup can also be expressed as the ratio of average fixed costs to average variable costs. Thus, equation (3) implies that the price increases if the change in average variable costs exceeds the average fixed costs multiplied by the percent quantity change.

8 To see this, note that $P = \frac{(F+VC)}{Q}$, where *VC* is total variable costs and the right side equals average costs. The derivative of the price with respect to quantity equals $\frac{dP}{dQ} = -\frac{(F+VC)}{Q^2} + \frac{MC}{Q}$, where *MC* is marginal costs. This expression implies that the derivative is negative if marginal costs are less than average costs.

## 3.2. Estimation Strategy

Section 3.1 showed that an increase in electricity demand could increase or decrease average electricity prices, depending on the steepness of the average variable cost curve. This subsection explains how we estimate the effect of demand on average prices.

Since data are available by utility, state, and year, we could estimate the following linear regression:

$$ln(P_{ist}) = \beta_0 + \beta_1 ln(RS_{ist}) + \delta_t + \alpha_{is} + \varepsilon_{ist} \quad (4)$$

where $P_{ist}$ is the average residential price for utility *i* operating in state *s* in year *t*, $RS_{ist}$ is residential sales, $\delta_t$ includes year fixed effects, $\alpha_{is}$ includes utility-state fixed effects, and $\varepsilon_{ist}$ is the idiosyncratic error term. The key coefficient of interest is $\beta_1$, which is the elasticity of the average price to residential sales. The year and utility-state fixed effects control for unobserved shocks that affect prices of all utilities proportionately in a particular year and for unobserved time-invariant utility-state attributes.

In equation (4), $\beta_1$ represents the effect of a 1 percent change in residential sales on the average price in the same year. In areas with retail competition, one might expect retail providers to adjust their rates fairly quickly in response to a change in demand. In areas with regulated retail rates, the utility may adjust rates only periodically, in which case demand changes in years prior to t may affect average prices in year *t*. For that reason, we estimate versions of equation (4) that include lags of residential sales or that aggregate annual observations to multiyear time periods. Note that, in these specifications, the estimated effect of sales on average prices may include transmission or distribution network investments needed to accommodate higher demand.

Estimating equation (4) by OLS suffers from the classic simultaneity problem: prices and quantities are determined jointly. Our objective is to identify the effects of demand on equilibrium prices—that is, the elasticity of average price to demand. However, given the utility-level data used to estimate equation (4), the quantity coefficient in equation (4) may be identified partly by a shift of the utility's variable cost curve, rather than movement along the curve. This situation would invalidate the interpretation of the sales coefficient as the elasticity of average price with respect to demand.

We take two approaches to address the simultaneity bias in equation (4) and support the interpretation of $\beta_1$ as the elasticity of average price to residential demand. First, we add variables to equation (4) that control for generation costs, which reduces the extent to which $\beta_1$ is identified by shifts of the variable cost curve. Specifically, we use the fuel price, $PF_{st}$, or natural gas price indexes described in Section 2 to control for generation costs.

Second, we use demand-shifters to instrument for residential sales in equation (4). Weather variables are correlated with residential electricity demand because many households use electricity for heating and cooling. In the literature on residential electricity demand (e.g., Davis 2008 and Fowlie et al. 2018), it is common to use cooling and heating degree days to predict residential demand. Using both variables to instrument for demand allows cold days to affect heating demand independently of the effect of warm days on cooling demand. This is an important consideration because the annual data used to estimate equation (4) includes within-year temperature variation and use of heating and cooling. In other words, including the two variables separately yields more accurate predictions of electricity demand than if we were to use a single index. The literature has established the relevance of the demand instrumental variables (IVs), and the exclusion restriction rests on the argument that, except in extreme weather events, weather does not affect the costs of supplying electricity.[9]

The first and second stages are:

$$ln(RS_{ist}) = \theta + \lambda_1 CDD_{st} + \lambda_2 (CDD_{st})^2 + \lambda_3 HDD_{st} + \lambda_4 (HDD_{st})^2 + \lambda_5 ln(PF_{st}) + \delta_t + \alpha_{is} + \varepsilon_{ist} \quad (5)$$

$$ln(P_{ist}) = \beta_0 + \beta_1 ln((\widehat{RS_{it}})) + \beta_2 ln(PF_{st}) + \delta_t + \alpha_{is} + \varepsilon_{ist} \quad (6)$$

where $CDD_{st}$ and $HDD_{st}$ are the cooling degree days and heating degree days for state s in year *t*.[10] The first stage includes linear and quadratic terms in *CDD* and *HDD* to improve the fit of the first stage.

Finally, we add to equation (6) the log of industrial electricity sales. This variable enables a joint test of two assumptions underlying the interpretation of $\beta_1$ as the elasticity of the average residential price to residential demand. The first assumption is that the determination of residential prices can be separated from commercial and industrial prices. This allows us to estimate a single equation predicting residential prices without simultaneously modeling commercial and industrial prices.

Of course, in the long run, fixed costs, such as transmission or distribution system upgrades, are spread across customer classes, and the average prices in the three sectors are determined jointly. The second underlying assumption is that the

9 To estimate persistence of *CDD* and *HDD*, we regress each variable on other first-stage independent variables, then test for autocorrelation of residuals and report results of those tests. Except for the squared *CDD* for the Western interconnection ($p < 0.09$), all p-values are below 0.01, indicating no evidence of autocorrelation.

10 Seasonal weather variation underlies the variation in the instruments, which are measured annually. For example, a hot summer would increase *CDD* without affecting *HDD*. Because electricity prices tend to be higher in the summer than in other months, CDD affects the average price via a compositional effect, since higher *CDD* raises the share of consumption occurring in the summer, and increases the consumption-weighed annual price. This situation implies that the first and second-stage coefficients on *CDD* may vary across utilities to the extent that seasonal price variation differs across utilities, and similarly for *HDD*. This issue affects the first-stage coefficients on *CDD* and *HDD* as well as the second-stage coefficient on residential sales, but it should not invalidate the instruments, since the effect of *CDD* and *HDD* on average price occurs via residential sales and not independently of residential sales.

instrumented residential demand should be uncorrelated with demand shocks in other sectors. If this assumption is not satisfied, the instrumented residential demand would be correlated with the omitted demand in other sectors. If this assumption is satisfied, $\beta_1$ represents the effect of residential sales on residential prices, holding fixed sales to other customer classes. Residential sales may affect prices for other customers, but this possibility lies outside our scope of analysis, given our interest in the effects of residential technology adoption on electricity bills for nonadopters.

Controlling for industrial demand and instrumenting for industrial demand using the employment-driven demand index presented in Section 2 addresses the possibility that the instruments are correlated with industrial sales (unfortunately, we are not aware of valid instruments for commercial demand, and we omit commercial demand from the analysis). The industrial demand index isolates variation in labor demand across manufacturing industries and over time, interacted with the industry's ratio of electricity consumption to employment. The underlying assumption is that manufacturing labor demand is uncorrelated with residential electricity demand.

We add the log of industrial sales to equation (6) to obtain the estimation equation:

$$ln(P_{ist}) = \beta_0 + \beta_1 ln((\widehat{RS_{it}})) + \beta_2 ln(PF_{st}) + \beta_1 ln((\widehat{IS_{it}})) + \delta_t + \alpha_{is} + \varepsilon_{ist}, \qquad (7)$$

where ( $\widehat{IS_{it}}$ ) is predicted industrial demand using cooling degree days, heating degree days, and the demand index as instruments. In equation (7), the same three instruments predict ( $\widehat{RS_{it}}$ ) in the first stage.[11]

## 3.3. Results

This section discusses the estimates of equations (6) and (7), focusing on the elasticity of price to demand, $\beta_1$. We report a negative and precisely estimated elasticity of around −0.4. According to expression (3), the negative elasticity indicates that when residential demand increases, the magnitude of the reduction in average fixed costs exceeds the increase in average variable costs.

### 3.3.1. Baseline Results

Column 1 in Table 3 reports estimates of equation (6) without instrumenting for residential sales. Observations are weighted by the utility's average number of residential customers, leading to the interpretation of $\beta_1$ as the customer-weighted average. The estimate of $\beta_1$ is −0.2, which is statistically significant at the 1 percent level. As discussed above, this estimate likely suffers from simultaneity bias, and the direction of the bias depends on the correlation between unobserved demand and supply shocks.

11 Note that we regress the log of the ratio of revenue to sales on the log of sales in equation (7). If instead we regress the log of revenue on log of sales, we get a coefficient of 0.637 ($p<0.01$) on log of residential sales and 0.00289 ($p>0.10$) on log of industrial sales. The sales coefficient indicates a similar elasticity of price to sales as that reported in Table 3.

Column 2 shows the IV estimate of $\beta_1$, which is about −0.4. That the magnitude is larger than in column 1 indicates that demand and supply shocks are positively correlated with one another. In other words, when a positive demand shock causes the demand curve to shift out, typically the average variable cost curve simultaneously shifts up, causing us to estimate a less negative elasticity of price with respect to demand. The coefficient on the weighted natural gas prices is positive, which is consistent with the intuition that an increase in natural gas prices causes the average variable cost curve to shift up, increasing average retail prices.

Appendix Table A1 reports the first stage of instrumenting for residential sales. Cooling and heating degree days affect residential consumption positively, as expected. Appendix Figure A1 shows a scatter plot of the log of residential sales against the predicted values from the first stage, which illustrates a strong correlation between the instruments and the endogenous residential sales.

Column 3 shows the results from estimating equation (7), which includes the log of industrial sales on the right-hand side and uses the industrial demand index to instrument for industrial sales (Appendix Table A1 shows the first-stage results). In column 3, the coefficient on residential sales is nearly the same as in column 2, indicating that the instrumented industrial sales are not strongly correlated with residential sales, and supporting the validity of the residential sales instruments. The coefficient on the industrial sales variable itself is positive and statistically significant at the 10 percent level, and the magnitude is substantially smaller than the residential sales coefficient. Thus, the IV estimates lie around −0.4.

### 3.3.2. Lagged Responses

Average prices may respond to lags of residential sales, either because retailer entry and exit responds gradually (in a competitive retail market) or the regulator adjusts prices sporadically (in a regulated environment). To allow for this possibility, we estimate three separate regressions using one-, two-, and three-year lags of demand, along with the corresponding lagged instruments in the first stage. Because current and lagged sales variables are highly correlated with one another (correlations all exceed 0.99), we add each lag in a separate regression and report the results in Table 4. The estimated coefficients decline in magnitude with longer lags, changing from −0.29 to −0.12. Nonetheless, even with a lag of three years, the coefficient remains negative and statistically significant at the 1 percent level. One possible explanation of the declining magnitude is that, following an increase in demand, utilities may receive regulatory approval to make capital upgrades, which are then folded into the rate base and prices are increased accordingly. We conclude that higher demand reduces average prices for at least three years, with the magnitude diminishing over time.

As an alternative approach to addressing lagged responses, we aggregate the data into two- or three-year periods. For each utility or state, we compute average prices, average fuel prices, and total demand over each multiyear period, and construct the instruments accordingly. The estimates remain consistent with the main findings in Table 3, with a coefficient of −0.4 (Table 5).

### 3.3.3. Heterogeneity by Ownership Type and Interconnection

Table 3 shows the sample-wide average elasticity of average price with respect to residential demand, and next we allow for heterogeneous elasticities by ownership type or interconnection. Table 6 assesses whether the elasticity differs for public utilities versus privately owned ones or cooperatives. The sample is the same as in Table 3, and we interact residential sales with an indicator equal to one if the utility is publicly owned. We treat the interaction term as endogenous, and the estimation includes the interactions of ownership type with the other instruments.

The results indicate statistically and economically meaningfully different relationships for public and other utilities. The average elasticity for public utilities (which account for about 60 percent of the sample) is the sum of the coefficient on the main effect and the coefficient on the interaction, which is –0.2 (although not reported, the sum is significant at the 1 percent level). This elasticity is smaller than the main estimate of –0.385, which could reflect systematic differences in cost or ownership structure, but unfortunately data limitations prevent investigation of the underlying causes. Instead, we note that the effect of technology adoption-related demand changes on average prices may depend on utility ownership type.

Table 7 considers whether the elasticity of average price to residential demand varies across interconnections. The elasticity for the East is similar to the full sample, and the magnitudes for the other two interconnections are larger. Unfortunately, the estimates for the other two regions are sufficiently noisy to prevent strong conclusions about variation across interconnections.

### 3.3.4. Controlling for Competition

Particularly for utilities that are not subject to cost-of-service regulation, the degree of competition with other utilities could affect the utility's average price as well as the effect of residential demand on average prices. Utilities facing greater competition are likely to charge lower prices. Competition may also reduce sales and reduce the steepness of the average variable cost curve (see Figure 6), causing demand to have a more negative effect on average prices.

Table 8 shows the results if we add controls for three proxies for competition. Column 1 is the same as column 6 of Table 3, except that it includes as an independent variable the number of utilities operating in the same state and year. The coefficient on this variable is negative, indicating that more competition reduces average prices, as expected. The coefficient on residential sales is nearly the same as in Table 3, which indicates that the level of competition (as proxied by the number of utilities) is not strongly correlated with predicted residential sales from the first stage.[12]

12 We have also tried approximating competition using sales of other utilities in the same state. However, the additional variable is strongly correlated with the utility's own sales, and neither coefficient on these variables is statistically significant.

Column 2 includes the interaction of residential sales with a dummy for states with retail competition according to EIA (EIA, 2024). The coefficient on residential sales is nearly the same as in Table 3, which again indicates that the level of competition does not strongly correlate with predicted residential sales.

Column 3 uses the Herfindahl-Hirschman Index (HHI) of utilities operating in the same state. The coefficient on the HHI index is positive but it is not precisely estimated, indicating that there is insufficient variation to identify the effect of the HHI on average prices.

### 3.3.5. Sample Sensitivity

From 2013 to 2018 and 2020 to 2022, the EIA 861 data contain two reporting groups: short form and long form. In those years, utilities with annual sales below 200,000 MWh report only total sales without distinguishing residential sales from other sectors. Consequently, the results reported thus far do not include the short-form utilities for those years. Figure 7 shows counts of utilities that report on the short form or long form. Roughly half of utilities report on the short form, but cumulatively these utilities account for just 14.3 percent of total residential sales in other years.

The reporting change could bias estimates of the residential sales elasticity if the elasticity differs systematically between short-form and long-form utilities. To assess whether this is the case, Table 9 reports results from the same estimation model as in columns 4–6 of Table 3 and observations from 1990 to 2022, except dropping utilities in all years that report on the short form from 2013 to 2018 or 2020 to 2022. The coefficient on residential sales is similar to that in Table 3, indicating that the variation in sample does not bias the estimates.

Finally, we test whether the elasticity of the average price to consumption changed during the sample. As discussed in Section 2, natural gas prices dropped substantially after 2008, which flattened the average variable cost curves. We expect the elasticity of average price to consumption to be more negative after 2008 than prior, which we can test by adding to equation (7) the interaction of the residential sales variable with the natural gas price, instrumenting for the interaction term (the instruments include corresponding interaction terms with the indicator variable). The coefficient on sales is –0.350, which is statistically significant at the 1 percent level, and the coefficient on the interaction term is –8.40e–06, which is not statistically significant. The negative interaction coefficient is consistent with expectations.

# 4. Simulating the Effect of Electricity Consumption on Average Prices

This section reports the results of an alternative analysis to the econometrics in the previous section, which is to use a computational model of electricity generation and simulate price changes caused by hypothetical demand changes. We summarize the structure of the model and present the simulation results.

## 4.1. Model Overview

The computational model has the same structure as that described in Linn and McCormack (2019), except that for the present analysis we extend the data to include all three interconnections instead of just the East, and to include the years 2002–2022 instead of 2002–2015.[13]

In the model, each generation unit's costs include nonfuel costs and fuel costs. Nonfuel costs include labor and materials. Fuel costs depend on the price of fuel and the efficiency with which the unit produces electricity by burning fuel. Both fuel and nonfuel costs vary across units, and fuel costs also vary over time in accordance with fuel prices.

Total fossil fuel-fired generation for each interconnection and simulated hour is exogenous, and we assume that generation from nuclear, hydroelectric, and renewables does not respond to electricity prices. The market is perfectly competitive and firms treat the equilibrium price as exogenous to their generation choices.

The model introduces constraints affecting a unit's minimum generation level and its ability to vary generation across hours. The owner of a generator chooses whether the unit operates each hour and if the unit operates, the owner chooses a generation level between unit and time-specific minimum and maximum values. The maximum generation level depends on time-varying factors, such as transmission constraints.

These features are designed to approximate behavior considered in models that explicitly characterize dynamics that arise due to startup costs and ramping constraints (Borrero et al. 2024 and Jha and Leslie 2025). In such models, firms desire to operate when demand and prices are likely to be high. Because they must incur startup costs to turn on and they face ramping constraints that prevent them from adjusting generation quickly, owners may choose to generate electricity during hours when prices are below their marginal costs. In other words, owners are willing to incur negative profits during some hours when prices are low if doing so allows them to operate their generators at full capacity during subsequent hours when prices are high.

To approximate these patterns, we simulate the model one day at a time and summarize how the daily equilibrium is obtained. At the beginning of each day, a system operator announces the exogenous peak hourly aggregate fossil generation for the day. The operator solicits bids, where a unit's bid includes a generation level and minimum price above which the unit generates the specified amount. The operator ranks the bids in order of increasing price and accepts bids to meet the forecast peak aggregate generation. Firms whose bids are accepted for peak hour generation must operate their units above their minimum levels during near-peak hours of the same day.

13 Unlike in that paper, we treat retirements and generator investments as exogenous, and compliance with environmental regulations is exogenous. Firms that own fossil fuel-fired generators face environmental regulations such as the Mercury and Air Toxics Standards, cap-and-trade programs for nitrogen oxides and sulfur dioxide, and emissions performance standards. We treat compliance with these regulations as exogenous because compliance decisions often involve large sunk costs, and the small demand changes we simulate are unlikely to affect compliance choices.

During hours far from the peak, the equilibrium is determined according to economic dispatch. In these hours, units operate at their maximum generation levels if the equilibrium price exceeds their marginal costs, and they operate at zero otherwise. The operator stacks the units in order of increasing marginal costs and selects the price such that combined generation equals aggregate fossil generation.

The distinction between peak and nonpeak hours, combined with the minimum and maximum generation constraints, reproduces the fact that generators often operate when their static marginal costs exceed the price. In the model, if a firm wants to operate its generator during the peak hour, it must also operate during near-peak hours.[14] This structure prevents units from turning off or shutting down repeatedly during near-peak and peak hours. Small gas- and oil-fired units are exempted from these constraints, and those units may turn on and off multiple times during a day. Linn and McCormack (2019) show that this model outperforms a simpler model that does not distinguish peak and near-peak hours, and instead assumes that equilibrium is determined in all hours via economic dispatch.

We simulate the model using observed fuel prices and aggregate fossil generation for each interconnection and hour from 2001 to 2022. For comparison with this baseline, we simulate a 1 percent decrease in aggregate fossil generation each hour. From the simulation output, we compute average variable costs for both scenarios.

Recall from equation (2) that the change in average retail price depends on the quantity change, the change in average variable costs, and the initial average retail price. We compute quantity changes and average variable costs from the simulation output, and we use EIA 861 data to compute average prices for each interconnection and year. Note that, for consistency with equation (2), we compute average variable costs as the ratio of the variable costs from fossil fuel-fired and nuclear generation to total generation (rather than fossil fuel-fired generation).

Equation (2) included the assumption that the consumption change does not affect fixed costs, which we relax in this analysis. Specifically, we consider scenarios in which solar photovoltaic adoption reduces consumption or EV adoption increases consumption. We estimate the change in fixed costs associated with quantity changes from Horowitz et al. (2018) for solar and from Cutter et al. (2021) for EVs.[15]

14 When firms submit their bids at the beginning of the day, they anticipate that they may earn negative hours during nonpeak hours. Therefore, they submit price bids sufficient to recover their losses during nonpeak hours. Therefore, the firm submits a peak hour price that is greater than its marginal operating costs.

15 Horowitz et al. (2018) estimate that the costs of upgrading the distribution network to incorporate rooftop solar may be $0.07 per watt of direct current. We compute the change in fixed costs by interconnection using their estimate and by assuming a 20 percent capacity factor for rooftop solar systems. Cutter et al. (2021) estimate distribution upgrade costs of $400 per kilowatt of EV battery capacity. We compute the change in fixed costs by interconnection using this estimate and assumptions on vehicle miles traveled and electricity consumption per mile described in Section 5 below.

This modeling includes a different set of assumptions than the analysis of the utility-level data in Section 3. The computational model includes assumptions on market structure and operating costs, whereas parameter estimates in Section 3 rest on the validity of the IV strategy. Moreover, the computational modeling explicitly holds fixed the costs associated with transmission and distribution, whereas the parameter estimates in Section 3 may include such cost changes.

## 4.2. Results

Panel A of Figure 8 shows the change in average variable costs caused by the demand decrease for each interconnection and simulation year. Lower demand reduces average variable costs, as expected, and the magnitude of the cost change is greatest in the mid and late 2000s. This pattern coincides with natural gas price variation (see Figure 5) as well as Figure 6, which shows that the average variable cost curve was substantially steeper in 2008 than in 2016. Consequently, lower demand causes a greater average variable cost decline when natural gas prices were high than when they were low.

Panel B reports the elasticity of average price to total demand that corresponds to the change in average variable costs from Panel A. The overall average price elasticity is about −0.4. The elasticity is less negative (that is, the magnitude is smaller) in the mid and late 2000s than in other years. This temporal variation is consistent with the analysis in Section 2 and the patterns in Panel A. The simulated demand increase reduces average fixed costs, which contributes to a negative elasticity. However, in the mid and late-2000s, the same demand increase causes a relatively large increase in average variable costs, which opposes the effect on average prices of the lower average fixed costs. The effect of higher average variable costs is not sufficiently large to cause an overall positive price elasticity, but nonetheless, it reduces the magnitude of the elasticity in the mid and late-2000s, when the average variable cost curves were relatively steep[16].

Note that we have evaluated counterfactual scenarios in which fossil generation increases by the same percentage for all hours of the day. Adoption of technologies such as rooftop solar or EVs likely affect demand more during some hours than others. Consequently, we have also simulated scenarios in which demand changes by the same magnitude as in the scenario reported in Figure 8. However, in these additional scenarios, hourly demand changes are scaled in proportion to typical solar generation profiles by interconnection as estimated in the PVWatts model, or in proportion to EV charging patterns from Northwest Power and Conservation Council (see the Appendix for details on the generation and charging profiles). We compute the price elasticity after including the distribution network investments that support rooftop solar or EV adoption, as described in Section 4.1.

16 If we estimate equation (7) and add the interaction of residential sales with an indicator for the years 2004-2008, the interaction coefficient is positive and statistically significant (about 0.03 with standard error). The positive coefficient and magnitude are consistent with the estimates in Figure 8.

Table 10 shows that the price elasticities for the demand decrease, rooftop solar, and EV scenarios are similar to one another. The magnitude of the elasticity is similar across the three interconnections, which reflects the similar steepness of the variable cost curves during most years, particularly when natural gas prices were low. The magnitude is typically somewhat smaller for the East interconnection than for the other interconnections, which reflects the relatively steep average variable cost curve in the East (see Figure 6).

Thus, the two approaches to estimate the effects of demand on average retail prices yield similar results. They rely on different assumptions about whether technology adoption affects demand uniformly or by different amounts across hours or seasons. The similarity supports the use of a single elasticity to estimate the effects of rooftop solar and EV adoption on average prices and household electricity bills, which we do in the next section.

# 5. Changes in Electricity Bills Caused by Rooftop Solar or EV Adoption

This section reports changes in electricity bills when rooftop solar or EV adoption affects aggregate electricity demand and average prices. Adopting rooftop solar reduces demand and raises average prices, whereas adopting EVs increases demand and reduces average prices. We first explain the methodology for computing bill changes by income group, and then we report the results. Adopting rooftop solar increases bills by a larger amount, relative to income, for low-income nonadopting households, exacerbating the regressivity of rooftop solar subsidies. In contrast, adopting EVs reduces bills more for low-income nonadopting households, offsetting the regressivity of EV subsidies.

## 5.1. Methodology

We calculate the effect of the subsidies on average prices and then compute changes in bills for all households in the RECS. Although the RECS data include detailed information about electricity consumption and total expenditure, unfortunately we do not know the rate structures that households face. To circumvent this problem, we make the simplifying assumption that all households in a state pay bills to a single utility. The utility's rate structure includes a fixed charge that does not vary across households and a variable rate per kWh of the household's consumption. Supporting the assumed rate structure is that roughly half of all US electric utilities offer such a two-part tariff and no other rate structures, and roughly 90 percent of utilities offer at least one such two-part tariff. That is, this rate structure approximates the rates that a majority of US households face.[17]

17 Many households face time-of-use price schemes in which the variable rate depends on the hour of day (typically the rate is higher during midday hours). The results reported in Section 5 are the same as assuming that the variable rate changes by the same amount in each hour of the day.

The total revenue earned by the representative utility is calculated by summing survey-weighted household expenditures. Similarly, the total electricity sales by the utility is the sum across observed household electricity consumption, also applying the sample weights. The state's average electricity price equals the ratio of total revenue to total consumption.

The total revenue from fixed charges equals the average fixed charge estimated from the OpenEI Utility Rate Database, multiplied by the total number of consumers. Subtracting this value from the total revenue gives the revenue from the variable portion of the bill. The variable rate is the ratio of the variable portion divided by total sales.

Table 2 shows summary statistics from the RECS households and estimated fixed charges and variable rates. The two rightmost columns in the table show the estimated fixed charges and variable rates. By construction, fixed charges and variable rates do not vary across households within a state, and the variation across income groups in the table arises from cross-state variation in the estimated values and income distributions. For example, households in the lowest group have the lowest average fixed charges, which is because states with low fixed charges have relatively high shares of households belonging to the lowest income group. Most households face variable rates of about $0.12 per kWh.

Having established baseline fixed charges and variable rates, we compute the changes in electricity demand caused by adopting rooftop solar or EVs. The RECS does not include data on electricity production from rooftop solar installations, and, for simplicity, we assume that for each RECS household with rooftop solar, the solar panels produce 100 percent of their reported annual electricity consumption (that is, households purchase zero net energy from the retailer after accounting for net metering). Likewise, for households with EVs, the RECS data do not distinguish electricity consumption for vehicle charging. Based on data from the 2022 National Household Travel Survey, we assume that each household drives its EV 10,000 miles per year and that the vehicle can be driven 3 miles per kWh of energy, which is a typical value for EVs. Using these assumptions and the reported solar panel and EV adoption in RECS, we compute total rooftop solar generation and EV charging consumption by state.

Finally, we compute the change in each household's bill caused by the average price changes. The average price ( $\overline{P_s}$ ) for state s equals the ratio of the fixed charge revenue (*FC*$_s$) to sales (*Qs*) plus the variable rate (*VRs*):

$$(\overline{P_s}) = \frac{FC_s}{Q_s} + VR_s. \tag{8}$$

If a state's total sales change from $Q_s$ to $Q'_s$, we use the estimated elasticity of average price with respect to consumption from column 6 of Table 3, which is –0.385, to compute the new price, ( $\overline{P_s}'$ ). The resulting price change for each state is:

$$(\overline{P_s}') - (\overline{P_s}) = \frac{FC'_s}{Q'_s} - \frac{FC_s}{Q_s} + VR'_s - VR_s. \tag{9}$$

Equation (8) holds for each state, and it includes two unknown variables: $FC'_s$ and $VR'_s$. To make further headway, we need to constrain the retailer's choices of these two variables. We consider two alternative scenarios: that the electricity retailer changes only the fixed charge or that the retailer changes only the variable rate.

In the scenario where the retailer changes only the fixed charge, $VR'_s = VR_s$, and equation (8) determines $FC'_s$. We compute the new fixed charge for each household by dividing $FC'_s$ by the number of households in the state.

Similarly, in the scenario where the retailer changes only the variable rate, $FC'_s = FC_s$, and equation (8) determines the new variable rate, $VR'_s$. We use this variable rate and the household's electricity consumption (net of rooftop solar generation and including EV charging, if any), to compute the household's new electricity bill.

Both scenarios assume that utilities adjust prices in response to changes in electricity consumption, reflecting the short-term effects of increased solar penetration or EV adoption—when large-scale infrastructure investments have not yet occurred. In the long term, however, the transmission and distribution systems will require upgrades to accommodate rising solar output or EV-related load growth. We include estimates of the short-term costs associated with integrating these technologies, which reflect the investments made at current adoption levels. The Appendix provides the details on the calculation of these Distribution Upgrade Costs (DUC). We assume that utilities recover these costs by passing them through to consumers and calculate the resulting distributional surcharge as an additional fee applied on top of either the simulated fixed charge ($FC_s$) or variable rate ($VR_s$), according to the scenario.

## 5.2. Rooftop Solar Results

Table 11 shows the national-level average results of simulating price and bill changes caused by the adoption of rooftop solar. The first row shows that rooftop solar reduces national electricity consumption by 3.8 percent. Total revenue, which equals household expenditure (see column "Without DUC") plus the distribution upgrade costs (column "DUC"), declines by a smaller amount—2.4 percent instead of 3.8 percent—because the consumption reduction affects only the variable portion of households' electricity bills.

Assuming a price elasticity of –0.385, a 3.8 percent decline in electricity consumption results in a 1.5 percent increase in the average price. The "Average annual fixed charge" row shows that total fixed charges increase by $12.55, assuming the utility applies a fixed distribution surcharge while holding the variable rate constant. In contrast, the bottom row shows a total increase of 0.15 cents per kWh if the utility adjusts the variable rate rather than the fixed charge. In both scenarios, the price increase is primarily driven by reduced electricity consumption, and the distribution surcharge accounts for less than 20 percent of the bill increases. Including these surcharges, fixed charges increase by 9.9 percent, while variable rates rise by 1.2 percent.

Figures 9 and 10 illustrate the effects on electricity bills by income group, whether the utility increases fixed charges or variable rates. Both figures show that the net effect of bill changes (black lines) are primarily driven by price increases resulting from reduced total electricity consumption (blue bars), with only a small portion attributable to DUC (maroon bars).

Panel A of Figure 9 displays the average ratio of bill changes to median income for households that adopt rooftop solar, assuming the retailer adjusts the fixed charge and applies a fixed distribution surcharge while leaving the variable rate unchanged. Although adopting households pay higher fixed charges and a distribution surcharge, their total bills are lower than if they had not adopted solar. Moving from left to right in the figure, the ratio of the bill change to income increases with income because the ratio of preadoption consumption to income decreases with income (that is, as Table 2 shows, the income-elasticity of electricity consumption is less than one). The magnitude increases more quickly across the lower income groups than the higher ones.

Panel B shows bill changes for nonadopters and for all households. For nonadopters, bills increase because of the higher fixed charges and a fixed distribution surcharge. These charges vary little across households in absolute terms, and the ratio of total charges to income declines with income, particularly for the lower-income groups.

Combining nonadopters and adopters in Panel B shows that, on average, adopting solar reduces electricity bills. The ratio of the bill change to income varies little across income groups, with the exception of the lowest income group, which experiences higher bills on average because adoption is so rare among that income group. Although solar reduces bills for the average household, the two panels show a sharp contrast between nonadopters—who experience higher bills, particularly for low-income households—and adopters, who experience lower bills.

Figure 10 is constructed similarly to Figure 9, except that in Figure 10 the fixed portion of the bill is held constant. The retailer adjusts the variable rate and applies a variable distribution surcharge. As in Figure 9, Panel B of Figure 10 shows larger bill increases for low-income nonadopters than for high-income nonadopters. The ratio of the bill change to income declines with income because the ratio of consumption to income also declines with income, and all households experience approximately the same increase in variable rates.

O'Shaughnessy et al. (2020) and Burger et al. (2020) find that rooftop solar subsidies are claimed disproportionately by high-income households. Thus, the bill changes for nonadopters caused by equilibrium price changes exacerbate the regressivity of the subsidies.

## 5.3. EV Results

Table 12 and Figures 11 and 12 present the simulation results for EV adoption. Table 12 shows that EV adoption increases residential electricity consumption by approximately 0.6 percent, reducing the average electricity price by 0.23 percent. Annual fixed charges fall by 0.68 percent when retailers adjust fixed charges and apply a fixed distribution surcharge while holding variable rates constant. Alternatively, variable rates fall by 0.07 percent when retailers adjust variable rates and apply a variable distribution surcharge instead. The distribution surcharge (column "DUC") has a relatively small effect on bills, contributing an additional $0.99 to the annual fixed charge or 0.01 cents per kWh to the variable rate.

Figures 11 and 12 show that the lower average prices disproportionately benefit low-income nonadopting households, regardless of whether retailers adjust fixed charges or variable rates. Panel A of Figure 11 shows that adopters pay higher bills because of the additional electricity consumption needed to charge their EVs as well as the distribution surcharge, which collectively outweigh the lower fixed charge. Panel B shows that for nonadopters, the increase in the distribution surcharge partially offsets the reduction in fixed charges. The ratio of bill change to income decreases with income, as both fixed charges and the distribution surcharge remain similar across income groups. Across all households (adopters and nonadopters), the ratio of the average bill change to income increases with income because the adoption rates are sufficiently high that the bill increases for adopters outweigh the bill decreases for nonadopters. As with solar, the combined bars hide the heterogeneous effects across adopters and nonadopters; for EVs, the nonadopters benefit from lower electricity prices, which disproportionately benefits low-income nonadopting households.

Figure 12 shows the results when the utility adjusts the variable rate and applies a variable distribution surcharge instead of a fixed surcharge. The patterns are similar to those in Figure 11, although in some cases the underlying reasons differ. Panel A shows that the ratio of the bill change to income decreases with income, because we assume that all households drive their EVs the same number of miles, which causes the level of the electricity bill change to differ little across households and the ratio to decrease with income. In Panel B, for nonadopters, the magnitude of the ratio of the bill change to income deceases with income because the income elasticity of consumption is less than one and all households experience approximately the same changes in variable rates.

Muehlegger and Rapson (2019) find that EV subsidies have largely benefited high-income households, since they are most likely to buy EVs and claim the subsidy.[18] We end this section by considering to what extent does the progressivity of the bill changes offset the regressivity of the EV subsidies themselves.[19]

18 Prior to the Inflation Reduction Act, federal subsidies were offered in the form of tax credits. Consequently, only households with sufficient federal tax liability could claim the full credit. This attribute of the subsidy, combined with the relatively high demand for EVs among high-income groups, caused the subsidy to be regressive overall. Under the Inflation Reduction Act, households with low federal tax liability claimed the full subsidy.

19 A full welfare analysis of the EV subsidies would require simultaneously modeling EV and electricity demand, which lies beyond the scope of this paper. Instead, we compare the transfers from federal taxpayers to EV buyers with the electricity bill changes.

Because we do not observe which RECS households actually claimed the subsidies, for simplicity we assume that all households with EVs claimed the full subsidy amount.[20] For each household, we compute the combined electricity bill change and subsidy receipt, and aggregate across households by income group in Figure 13.

Panel A of Figure 13 shows that including the EV subsidy causes total electricity expenditure, net of the subsidy, to be negative for all households. The ratio of the magnitude of the expenditure change to income decreases with income. In Panel B, across all households, the ratio of the expenditure changes to income varies little across income groups (excluding the lowest group, which experiences a large expenditure decline). Recall that the income changes caused by the subsidy itself are regressive, since high-income households are more likely to adopt EVs than are low-income households (see Table 2). Thus, the progressivity of the bill changes for nonadopters is sufficiently strong to offset the regressivity of the EV subsidy for adopters.

## 5.4. Solar and EV Results for Alternative Parameter Assumptions

Section 5.1 describes the key parameter assumptions for estimating the effects of solar or EV adoption on household-level electricity bills. This subsection summarizes additional estimates that rely on alternative parameter assumptions, which are reported in the Appendix.

The econometric analysis of utility-level data and the simulations of the generation model yield estimated elasticity of retail prices with respect to consumption of about −0.385. Hypothetically, if the magnitude of the price elasticity is larger than that, the magnitudes of the changes in fixed charges or variable rates would be larger than reported in Sections 5.2 and 5.3. Because the ratio of electricity consumption to income decreases with income, the larger changes in variable rates could exacerbate the regressivity for nonadopters of solar (and enhance the progressivity for nonadopters of EVs).

Appendix Figures A3 through A6 show that the qualitative patterns of electricity bill changes across income groups are similar if we assume an elasticity of average price with respect to consumption of −0.2 or −0.6. The higher elasticity does not significantly alter the patterns for either solar or EV adopters, but it amplifies the effects for nonadopters—resulting in larger bill increases for solar nonadopters and greater bill reductions for EV nonadopters.

20 A household may not claim the full subsidy, because it is ineligible (for example, it has insufficient federal tax liability) or for other reasons. Our assumption that all households claim the subsidy causes us to overestimate total uptake of the subsidy. However, although the degree of overestimation of uptake may be correlated (positively or negatively) with household income, the conclusion about the overall progressivity in Figure 13 is not affected by this assumption, since few low-income households own EVs.

We use data from the OpenEI Utility Rate Database to calculate fixed and variable electricity charges in Sections 5.2 and 5.3. As an alternative approach, we estimate these components by using household-level observations in RECS and regressing household electricity expenditures on household consumption and a constant, estimating a separate regression for each state. The estimated consumption coefficient approximates the variable charge, while the intercept captures the effective fixed cost faced by households. This intercept may reflect the fixed charges as well as programmatic subsidies.

To compare the results from the two approaches, we focus on the variable charge. Appendix Figure A7 compares calculated and regression-estimated variable electricity charges across the contiguous US states. The approaches yield similar spatial patterns: higher charges in the Northeast and on the West Coast. The estimates differ from one another in some states, such as California and New York, which frequently employ tiered or time-of-use pricing, which the regression model cannot incorporate.[21] Although discrepancies exist between the two approaches, the regression-estimated variable charges produce similar patterns of electricity bill changes across income groups. Appendix Figures A8 and A9 illustrate this consistency under an elasticity of −0.385 for both solar and EV adoption scenarios.

Using the calculated fixed and variable charges, we simulate alternative scenarios to compare electricity bill patterns across income groups under different consumption changes. In the solar scenario, we assume rooftop systems offset 50 percent of household electricity consumption, rather than full displacement (net-zero grid usage) as in Section 5.2. Appendix Figures A10 and A11 show similar patterns but with bill impacts roughly half as large for both adopters and nonadopters.

In Section 5.3, we assume that all households drive their EVs 10,000 miles each year. As an alternative, we adjust miles traveled by income assuming an income elasticity of 0.2, which is consistent with the National Household Travel Survey data. Appendix Figures A12 to A13 mirror the patterns in Section 5.3 but show weaker effects for lower-income groups—resulting in smaller bill increases for adopters and slightly larger reductions for nonadopters.

As an alternative to the assumptions in Sections 5.2 and 5.3, we assume a single national utility in which all households, regardless of state of residence, face the same fixed and variable rates. This setup allows us to illustrate how much of the variation in bill changes across income groups is driven by differences in consumption rather than cross-state variation of fixed or variable rates. Appendix Figures A14 through A17 show patterns similar to those in Sections 5.2 and 5.3 for solar and EV adoption, but with amplified effects. For solar, nonadopters, especially in the lowest income group, face larger bill increases. For EVs, adopters see greater bill increases, while nonadopters face smaller reductions, with the largest impacts observed among the lowest income group.

21 The regression approach may overestimate variable costs in states with high variation in household usage and increasing block pricing, due to factors such as climate or appliance use. The approach may underestimate variable rates in states with more uniform usage patterns, such as New York.

# 6. Conclusions

This paper evaluates how policies that promote household adoption of GHG-mitigating technologies, such as rooftop solar panels or EVs, affect electricity prices and welfare of nonadopters. A stylized model of retail electricity pricing indicates that if the variable cost curve for generating electricity is sufficiently flat (or, equivalently, marginal costs are less than average costs), technology adoption that reduces aggregate demand causes average electricity prices to increase. Statistically analyzing utility-level data or simulating an electricity operation model indicates that this condition holds, and that reducing demand causes average prices to increase. We observe the negative relationship between demand and prices over a period of several decades, which includes substantial variation in fuel prices, generator technology, and regulation.

Based on the estimated effects of consumption on average prices, we simulate the effects of solar panel or EV adoption on electricity bills of nonadopters, using these examples to illustrate the effects of adopting technologies that reduce or increase electricity demand. Adopting solar panels reduces demand and raises prices, disproportionately increasing bills of low-income nonadopters. In contrast, adopting EVs raises demand and reduces prices, particularly benefiting low-income nonadopters. High-income households are more likely to adopt EVs and benefit directly from the subsidies than are low-income households, and the equilibrium price effect is sufficiently large to offset the direct regressivity of the subsidies themselves.

Regions with high levels of solar or EV penetration, such as California, have experienced contentious debates over reforming rate structures to balance reliability, environmental, cost, and equity objectives. Our results indicate that adopting rooftop solar or other technologies that reduce demand will put upward short-run pressure on retail rates. Our analysis includes the grid upgrades necessary to accommodate current levels of technology adoption. In the long run, the necessary grid investments are likely substantial, but nonetheless the magnitudes are uncertain and could be a useful direction for future research.

The finding that increasing demand causes electricity prices to decrease may partially resolve a puzzle apparent in aggregate electricity data. Over the past few decades, the United States has experienced a notable increase in residential electricity retail prices, coupled with a recent decline in residential demand growth demand (Section 2 below illustrates this pattern). This shift raises questions about the relationship between residential electricity consumption and retail pricing, particularly in a regulated utility environment. Our analysis of electricity retail data relies on relatively short-term and within-utility and year variation to identify the effect of electricity demand on average prices, and the results indicate that declining demand may increase average aggregate prices over short time horizons. Investigating the long-run causes of rising prices is left for future work.

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# Tables and Figures

## Table 1. Summary Statistics for Utility-Level Data, 1990–2022

| Variable | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| Price ($/kWh) | 0.064 | 0.031 | 0.005 | 0.569 |
| Residential sales (MWh) | 583400.4 | 2398114 | 1 | 6.95e+07 |
| Industrial sales (MWh) | 415034.9 | 1727122 | 1 | 3.32e+07 |
| Cooling degree days | 1167 | 787 | 0 | 5101 |
| Heating degree days | 5220 | 2187 | 79 | 11632 |
| Industrial electricity demand (MWh) | 2.21e+07 | 2.00e+07 | 334834.4 | 1.06e+08 |
| Weighted natural gas price ($/mmBtu) | 0.643 | 0.857 | −0.0001 | 6.710 |

Notes: The number of observations is 62,278. Average residential price is calculated as the revenue from residential customers divided by electricity sales. The weighted natural gas price is defined as the state-year natural gas price ($/mmBtu) multiplied by the share of natural gas in total fossil fuel consumption (measured in mmBtu). Industrial electricity demand is computed from county-level employment and industrial-level electricity consumption. Weighted fuel price is the consumption-weighted average price across coal, natural gas, and oil prices, by state and year.

## Table 2. RECS Summary Statistics: Means by Household Income Group

| Income Group | Total Customers (Millions) | Annual Electricity Consumption (Mwh) | Annual Electricity Expenditure (US$) | Percent of Electricity Expenditure to median income (%) | Rooftop solar adoption (%) | EV ownership (%) | Energy-consuming area (1000 sft) | Cooling degree days | Heating degree days | Estimated fixed charge (US$) | Estimated variable rate (US$ per kwh) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **less than $12,499** | 11.71 | 8.51 | 1113 | 13.25 | 0.63 | 0.51 | 1.15 | 1759 | 3613 | 142.53 | 0.120 |
| **$12,500–$24,999** | 13.16 | 8.78 | 1137 | 5.95 | 1.07 | 0.44 | 1.33 | 1708 | 3704 | 145.81 | 0.119 |
| **$25,000–$39,999** | 17.91 | 9.52 | 1219 | 3.78 | 2.09 | 0.56 | 1.49 | 1810 | 3594 | 142.67 | 0.119 |
| **$40,000–$59,999** | 19.59 | 9.96 | 1286 | 2.57 | 2.10 | 0.71 | 1.67 | 1760 | 3650 | 143.58 | 0.120 |
| **$60,000–$74,999** | 12.84 | 10.57 | 1373 | 2.05 | 3.00 | 0.96 | 1.77 | 1712 | 3794 | 144.87 | 0.121 |
| **$75,000–$99,999** | 14.86 | 10.91 | 1433 | 1.66 | 3.71 | 1.46 | 1.95 | 1616 | 3862 | 146.13 | 0.122 |
| **$100,000–$149,999** | 16.53 | 11.82 | 1553 | 1.29 | 4.78 | 1.88 | 2.19 | 1579 | 3897 | 148.49 | 0.124 |
| **$150,000 or more** | 16.83 | 13.66 | 1834 | 0.87 | 4.93 | 4.80 | 2.74 | 1604 | 3735 | 149.68 | 0.126 |

Notes: The table reports the mean values for each income group, weighted by sample weights. Heating and cooling degree days are calculated using a base temperature of 65 degrees Fahrenheit. The sample includes 18,496 households. Median income for each income group is computed from the American Community Survey.

## Table 3. Estimated Elasticity of Residential Retail Price to Residential Demand

| | (1)<br>OLS | (2)<br>IV | (3)<br>IV with industrial sales |
|---|---|---|---|
| Residential sales | −0.131***<br>(0.0228) | −0.392***<br>(0.0325) | −0.393***<br>(0.0359) |
| Industrial sales | | | 0.00993<br>(0.0173) |
| Cooling degree days | | 5.80e−06<br>(2.15e−05) | |
| Cooling degree days squared | | 3.88e−08***<br>(6.44e−09) | |
| Heating degree days | | 8.02e−05***<br>(6.76e−06) | |
| Heating degree days squared | | −3.00e−09***<br>(4.33e−10) | |
| Industrial demand index | | | |
| Weighted gas price | 0.0103***<br>(0.00259) | 0.0108***<br>(0.00286) | 0.0117***<br>(0.00340) |
| Constant | −0.787***<br>(0.260) | | |
| Observations | 62,278 | 62,192 | 62,192 |
| R-squared | 0.935 | 0.924 | 0.924 |
| Number of utility-states | 2,619 | 2,533 | 2,533 |
| Cragg-Donald Wald F statistic | | 246.32 | 119.596 |
| Hansen J statistic | | 35.260 | 35.644 |

Notes: The number of observations is 62,278. Average residential price is calculated as the revenue from residential customers divided by electricity sales. The weighted natural gas price is defined as the state-year natural gas price (US$/mmBtu) multiplied by the share of natural gas in total fossil fuel consumption (measured in mmBtu). Industrial electricity demand is computed from county-level employment and industrial-level electricity consumption. Weighted fuel price is the consumption-weighted average price across coal, natural gas, and oil prices, by state and year.

## Table 4. Estimated Elasticity of Residential Retail Price to 1-, 2-, and 3-Year Lag of Residential Demand

| | (1)<br>1-year lag | (2)<br>2-year lag | (3)<br>3-year lag |
|---|---|---|---|
| Lag residential sales | −0.296***<br>(0.0351) | −0.213***<br>(0.0335) | −0.194***<br>(0.0381) |
| Lag industrial sales | −0.00799<br>(0.0167) | −0.0140<br>(0.0169) | −0.00597<br>(0.0176) |
| Weighted gas price | 0.0113***<br>(0.00279) | 0.0115***<br>(0.00272) | 0.0121***<br>(0.00267) |
| Observations | 52,906 | 52,906 | 52,906 |
| R-squared | 0.926 | 0.928 | 0.928 |
| Number of utility-states | 2,404 | 2,404 | 2,404 |
| Wald F statistic | 96.113 | 101.855 | 115.009 |
| Hansen J statistic | 60.638 | 78.546 | 92.904 |

Notes: Standard errors are in parentheses, clustered by utility. Specifications are the same as in column 3 of Table 3 except using the lags of residential and industrial sales indicated in the column headings. *** p<0.01, ** p<0.05, * p<0.1.

## Table 5. Estimated Elasticity of Residential Retail Price to Residential Demand Using 2- or 3-Year Aggregated Data

| | (1)<br>2-year aggregation | (2)<br>3-year aggregation |
|---|---|---|
| Residential sales | −0.454***<br>(0.0565) | −0.693***<br>(0.0984) |
| Industrial sales | 0.0198<br>(0.0197) | 0.0465*<br>(0.0258) |
| Weighted gas price | 0.0102**<br>(0.00409) | 0.0152**<br>(0.00630) |
| Observations | 32,443 | 22,020 |
| R-squared | 0.924 | 0.882 |
| Number of utility-states | 2,518 | 2,498 |
| Wald F statistic | 54.683 | 34.505 |
| Hansen J statistic | 28.293 | 12.238 |

Notes: Standard errors are in parentheses, clustered by utility. Specifications are the same as in column 3 of Table 3, except that the data are aggregated to 2 or 3-year time periods. *** p<0.01, ** p<0.05, * p<0.1.

## Table 6. Estimated Elasticity by Ownership Type

| | **(1)**<br>**Ownership interaction term** |
|---|---|
| Residential sales | −0.408***<br>(0.0393) |
| Industrial sales | 0.0236<br>(0.0191) |
| Residential sales×public | 0.146***<br>(0.0412) |
| Weighted gas price | 0.0131***<br>(0.00349) |
| Observations | 59,611 |
| Number of utility-states | 2,423 |
| R-squared | 0.927 |
| Wald F statistic | 68.101 |
| Hansen J statistic | 92.775 |

Notes: Standard errors in parentheses, clustered by utility. The specification is the same as in column 3 of Table 3, except that it includes the interaction of residential sales with an indicator for public utility. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

## Table 7. Estimated Elasticity by Interconnection

| | ERCOT | East | West |
|---|---|---|---|
| Residential sales | −0.309<br>(0.210) | −0.367***<br>(0.0326) | −0.396*<br>(0.216) |
| Industrial sales | 0.150<br>(0.142) | −0.0106<br>(0.0147) | 0.0765<br>(0.0772) |
| Weighted gas price | | 0.00137<br>(0.00286) | 0.0365<br>(0.0265) |
| Observations | 3,048 | 51,050 | 5,513 |
| R-squared | 0.841 | 0.931 | 0.880 |
| Number of ids | 128 | 2,066 | 229 |
| Cragg-Donald Wald F statistic | 0.546 | 127.594 | 5.466 |
| Hansen J statistic | 1.300 | 54.953 | 9.529 |

Notes: Standard errors are in parentheses, clustered by utility. Specifications are the same as in column 3 of Table 3 except using the lags of residential and industrial sales indicated in the column headings. *** p<0.01, ** p<0.05, * p<0.1.

## Table 8. Controlling for Competition

| | (1) | (2) | (3) |
|---|---|---|---|
| Residential sales | –0.400***<br>(0.0348) | –0.510***<br>(0.0835) | –0.390***<br>(0.0351) |
| Industrial sales | 0.0107<br>(0.0170) | 0.0282<br>(0.0239) | 0.00604<br>(0.0174) |
| Number of utilities | –0.000718***<br>(0.000244) | | |
| Sales of other utilities in the same state | | 3.919*<br>(2.117) | |
| HHI | | | –1.63e-05***<br>(4.63e-06) |
| Weighted gas price | 0.0116***<br>(0.00344) | 0.0112***<br>(0.00371) | 0.0125***<br>(0.00337) |
| Observations | 62,192 | 62,192 | 62,192 |
| R-squared | 0.924 | 0.912 | 0.925 |
| Number of utility-states | 2,533 | 2,533 | 2,533 |
| Cragg-Donald Wald F statistic | 124.066 | 45.348 | 121.312 |
| Hansen J statistic | 32.301 | 25.785 | 40.792 |

Notes: Standard errors in parentheses, clustered by utility. Specifications are the same as column 3 of Table 3, except that they include the variables indicated in the row headings. Number of utilities is the number of utilities with positive retail sales in the same state and year. HHI is the Herfindahl-Hirschman Index. *** p<0.01, ** p<0.05, * p<0.1

## Table 9. Sample Includes Only Long-Form Utilities

| | **Only long-form utilities** |
|---|---|
| Residential sales | −0.427***<br>(0.0496) |
| Industrial sales | 0.0274<br>(0.0227) |
| Cooling degree days | |
| Cooling degree days squared | |
| Heating degree days | |
| Heating degree days squared | |
| Industrial demand index | |
| Weighted gas price | 0.00545<br>(0.00404) |
| Constant | |
| Observations | 32,418 |
| R-squared | 0.931 |
| Number of utility-states | 1,061 |
| Cragg-Donald Wald F statistic | 73.025 |
| Hansen J statistic | 28.117 |

Notes: Standard errors in parentheses, clustered by utility. The specification is the same as column 3 of Table 3, except that the sample includes only long-form utilities. *** p<0.01, ** p<0.05, * p<0.1.

## Table 10. Simulated Elasticity of Price to Quantity Change

| | 1 percent demand decrease | Rooftop solar adoption | EV adoption |
|---|---|---|---|
| ERCOT | −0.42 | −0.39 | −0.42 |
| East | −0.37 | −0.34 | −0.36 |
| West | −0.41 | −0.39 | −0.40 |

Notes: The table reports the elasticity of the retail price with respect to fossil generation quantity for the interconnection in the row heading and the scenario in the column heading. The first column reports the elasticity of the electricity price for a 1 percent demand decrease each hour from 2001–2022. The second column reports the elasticity for rooftop solar adoption that reduces electricity demand by the same total amount across all years as in the first column. The demand decrease is scaled to hourly rooftop solar production for a typical installation in each interconnection, as estimated by PVWatts. The third column reports the elasticity assuming an increase in EV adoption that raises electricity demand by the same magnitude as in the first column, except that the demand increase is scaled to EV charging profiles from the Northwest Power Conservation Council. Calculations assume that the retail markup (difference between retail price and variable fuel costs, divided by price) is 0.76. The second and third columns include distribution upgrade costs associated with rooftop solar and EV adoption from Horowitz et al. (2018) and Cutter et al. (2021).

## Table 11. Aggregated Simulation Results for Rooftop Solar

| | Estimated (E) | Simulated (S) | | | Percent change (%) |
|---|---|---|---|---|---|
| | | Without DUC | DUC | Total | (total S-E)*100/E |
| Total electricity consumption (10,000,000 MWh) | 5.16 | 4.96 | | 4.96 | –3.84 |
| Total revenue (billion US$) | 7.00 | 6.78 | 0.01 | 6.79 | –2.35 |
| Average price (cents per kWh) | 13.72 | 13.95 | | 13.95 | 1.48 |
| Average annual fixed charge (US$) | 145.52 | 156.23 | 1.85 | 158.07 | 9.89 |
| Average variable rate (cents/kWh) | 12.14 | 12.27 | 0.02 | 12.29 | 1.16 |

Notes: The table reports the weighted mean values across states using household survey weights. Values in the "Estimated" column are summary statistics computed from the RECS data. Values in the "Total" column under "Simulated" report the net effects of rooftop solar adoption on electricity prices and bills, which can be decomposed into two components: effects due to consumption (without DUC) and effects due to distribution upgrade costs (DUC column). The column "Percent change" is the percent change between the simulated total and estimated columns. The row "Average annual fixed costs" reports the simulated annual fixed charge assuming the variable rate is unchanged. The row "Average variable cost" reports the simulated average variable rate assuming fixed charges are unchanged.

## Table 12. Aggregated Simulation Results for EVs

| | Estimated (E) | Simulated (S) | | | Percent change (%) |
|---|---|---|---|---|---|
| | | Without DUC | DUC | Total | (total S-E)* 100/E |
| Total electricity consumption (10,000,000 MWh) | 5.16 | 5.20 | | 5.20 | 0.59 |
| Total revenue (billion US$) | 7.00 | 7.03 | 0.008 | 7.04 | 0.44 |
| Average price (cents per kWh) | 13.72 | 13.68 | | 13.68 | −0.23 |
| Average annual fixed charge (US$) | 145.52 | 143.72 | 0.99 | 144.71 | −0.68 |
| Average variable rate (cents/kWh) | 12.14 | 12.11 | 0.01 | 12.13 | −0.07 |

Notes: The table reports the weighted mean values across states using household survey weights. Values in the "Estimated" column are summary statistics computed from the RECS data. Values in the "Total" column under "Simulated" report the net effects of EV adoption on electricity prices and bills, which can be decomposed into two components: effects due to consumption (without DUC) and effects due to distribution upgrade costs (DUC column). The column "Percent change" is the percent change between the simulated total and estimated columns. The row "Average annual fixed costs" reports the simulated annual fixed charge assuming the variable rate is unchanged. The row "Average variable cost" reports the simulated average variable rate assuming fixed charges are unchanged.

## Figure 1. Total Residential Sales and Average Electricity Price, 1990–2022

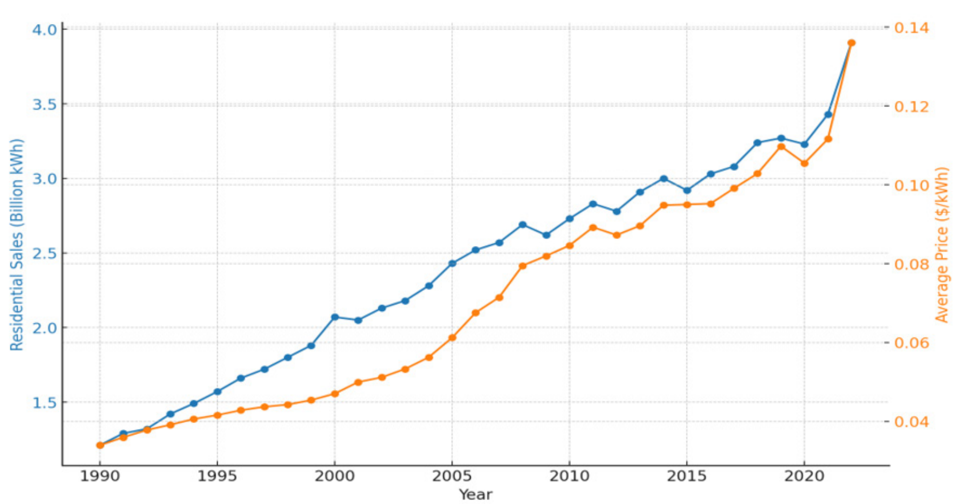


**Figure 2. Distribution of Average Prices by Interconnection, 1990–2022**

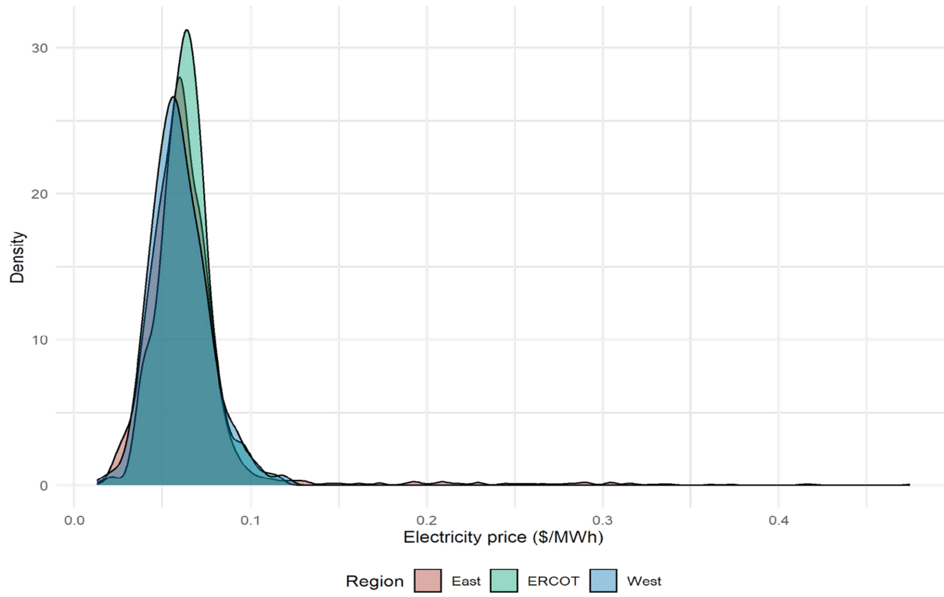
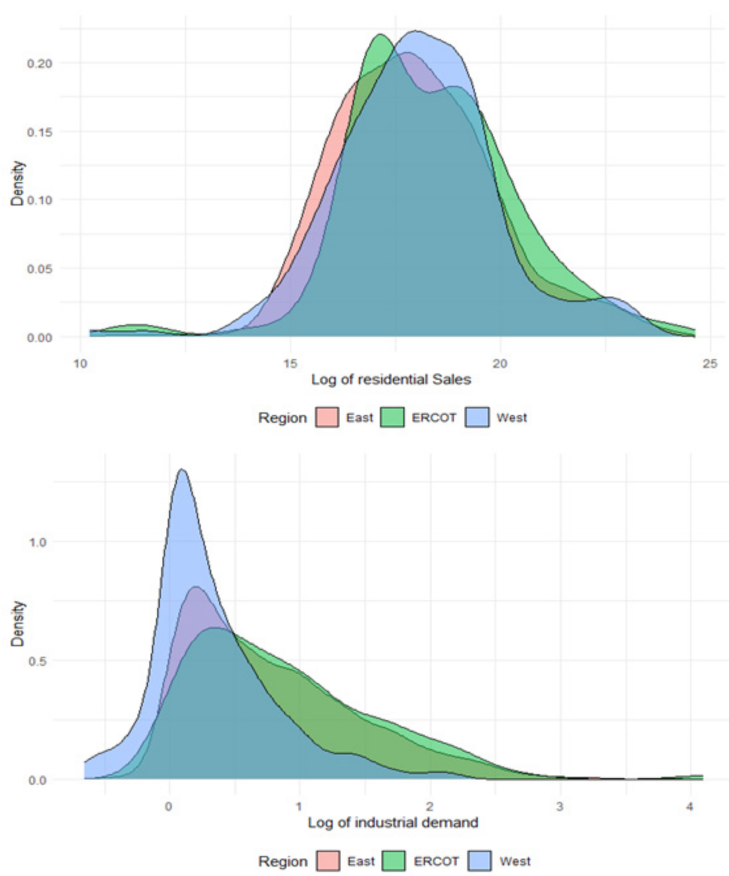
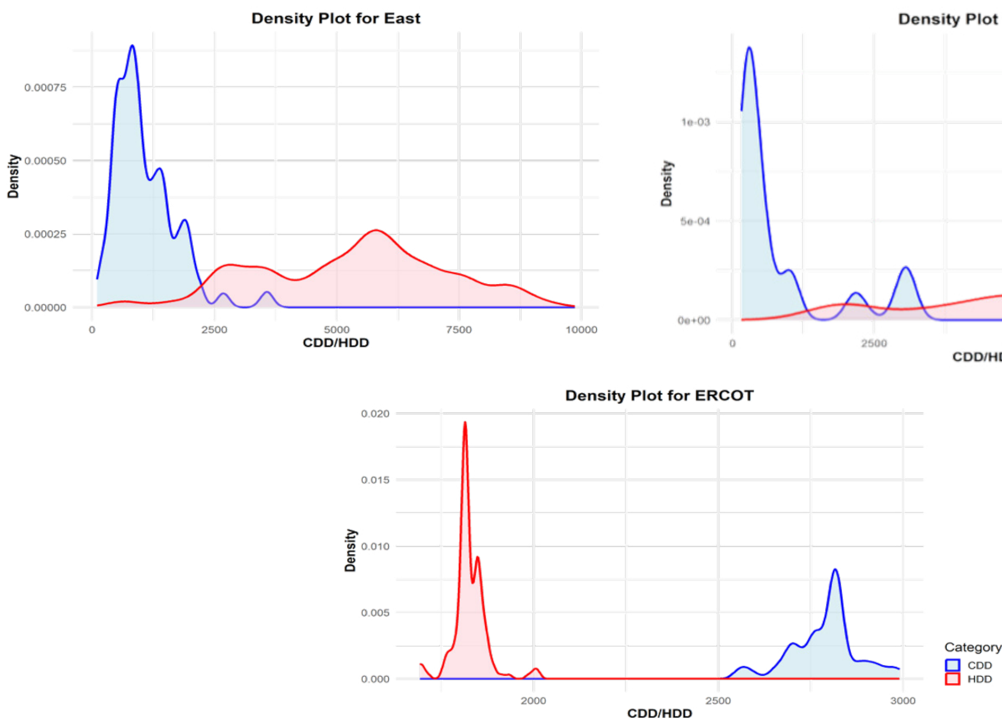


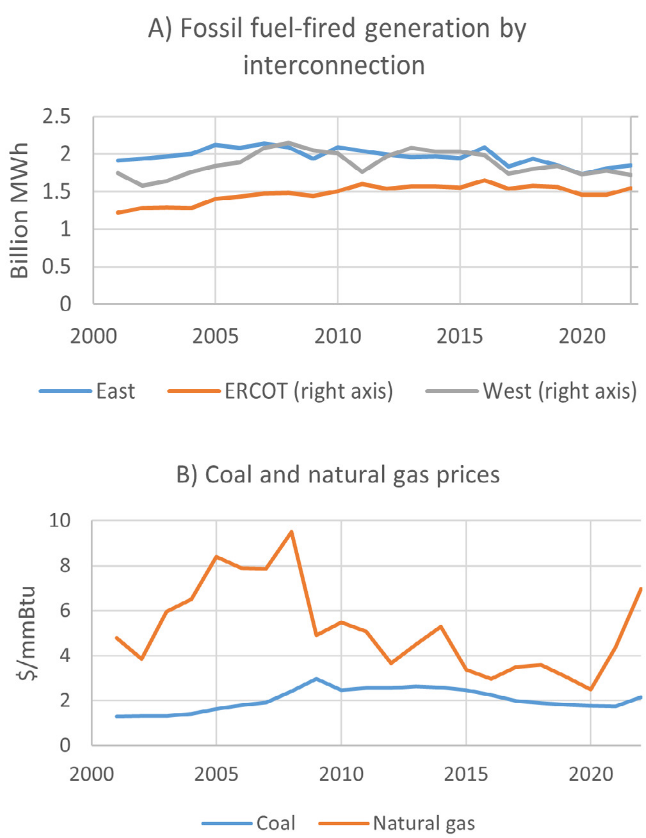

**Figure 3. Distributions of Log Residential Sales and Log Industrial Sales by Interconnection, 1990–2022**



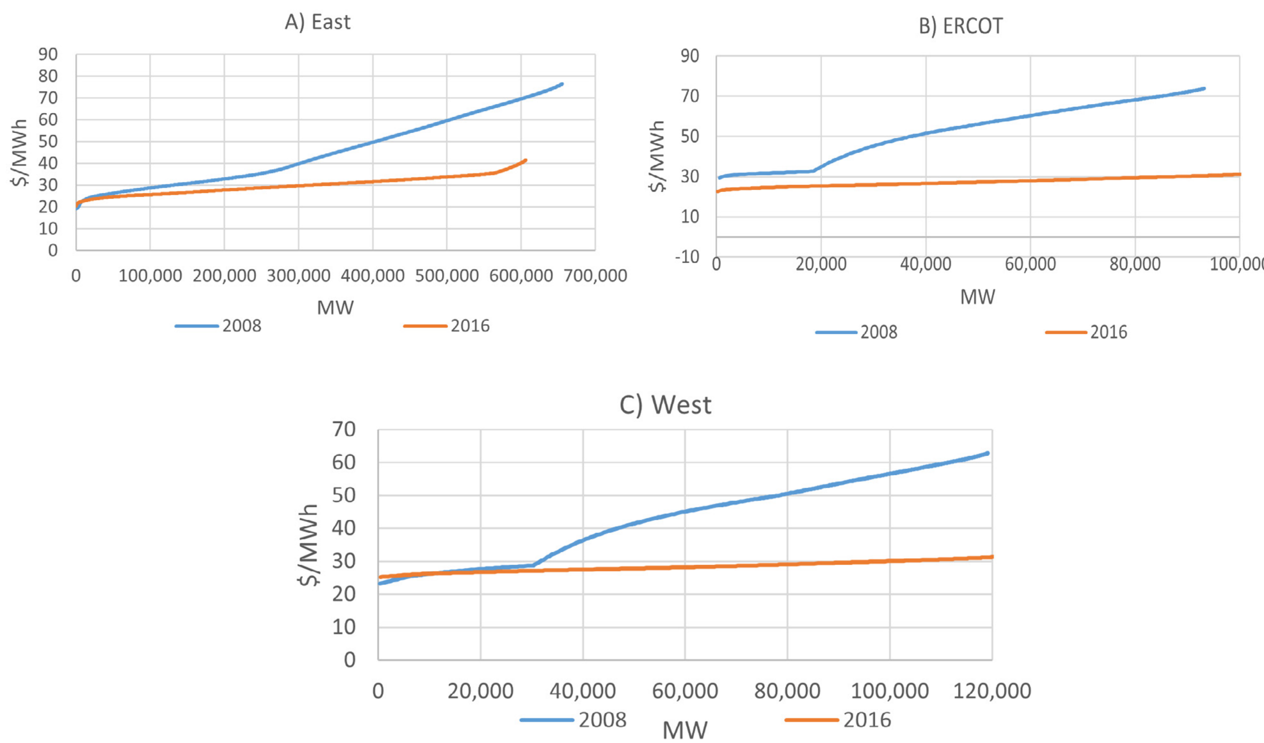
## Figure 4. Distributions of Heating and Cooling Degree Days by Interconnection, 1990–2022



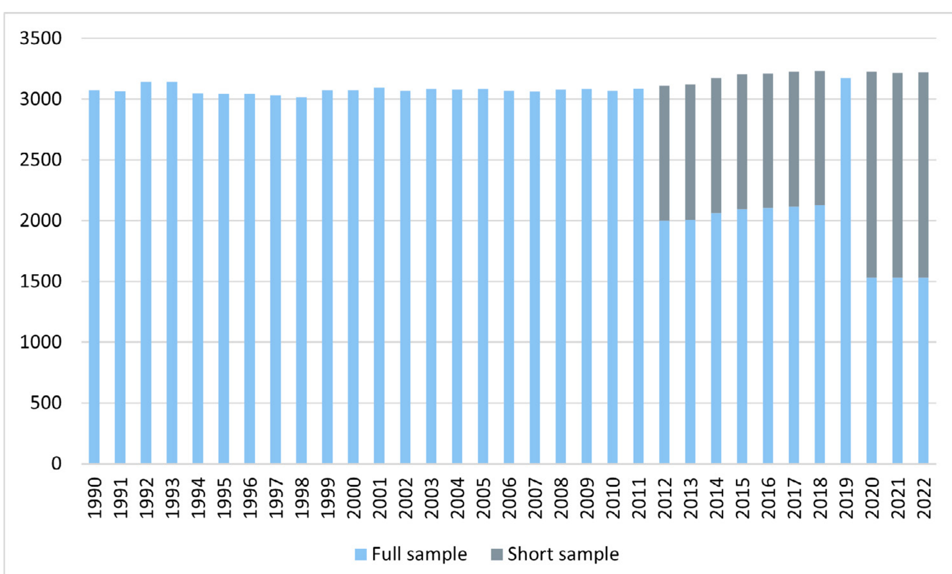

## Figure 5. Fossil Fuel-Fired Generation and Fuel Prices, 2001–2022



## Figure 6. Average Variable Costs by Interconnection, 2008 and 2016

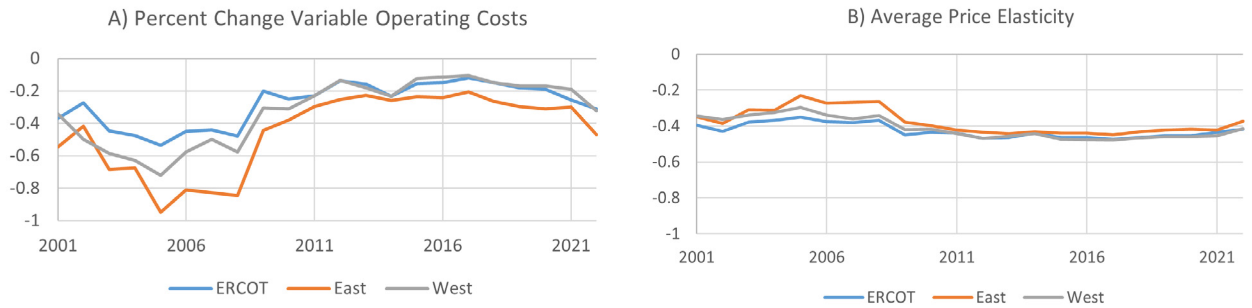



## Figure 7. Counts of Short-Form and Long-Form Utilities



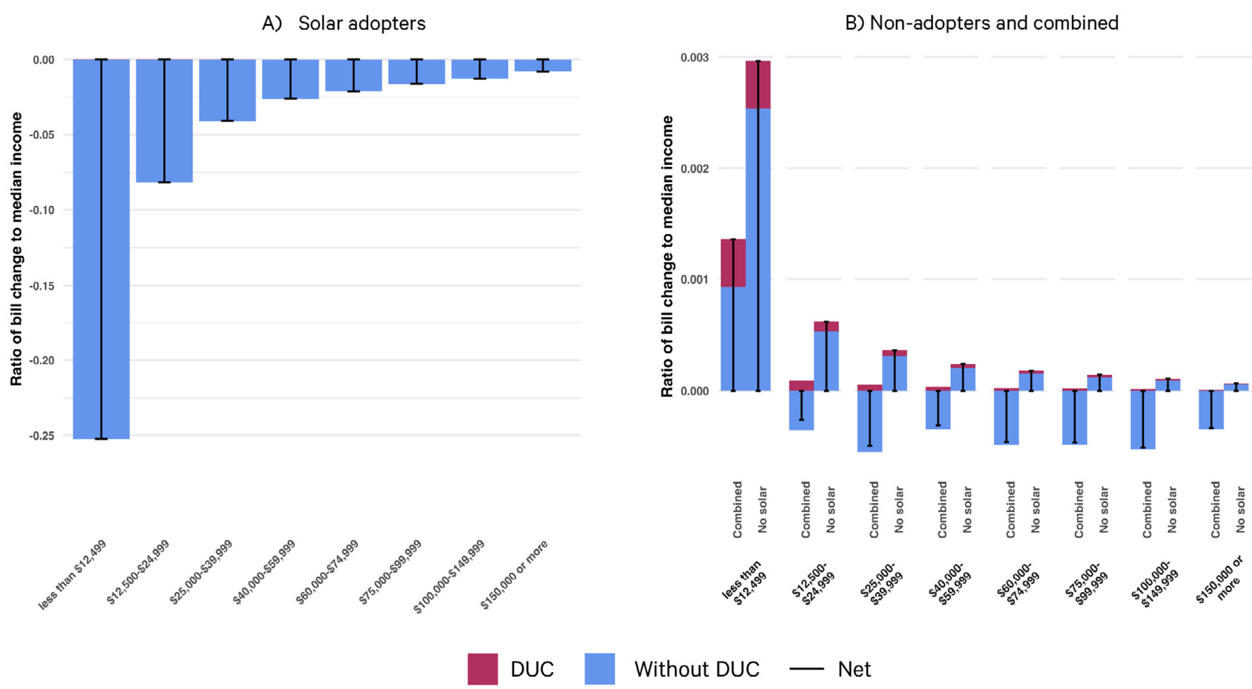

Note: Blue bars indicate long-form utilities and gray bars indicate short-form utilities.

## Figure 8. Average Variable Costs by Interconnection, 2008 and 2016



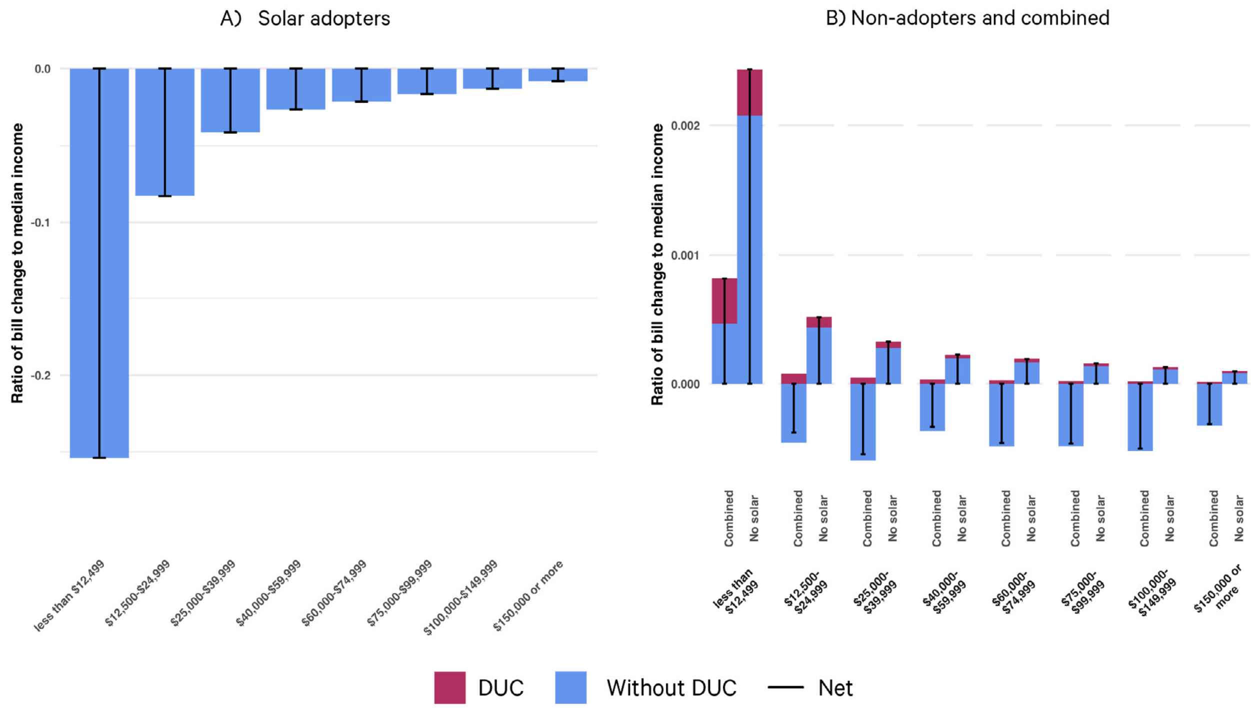

Notes: Panel A reports the simulated percent change in average variable operating costs caused by a 1 percent demand decrease for all hours of the year, by interconnection and year. Panel B shows the estimated elasticity of the average price with respect to residential demand.

## Figure 9. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Fixed Charges



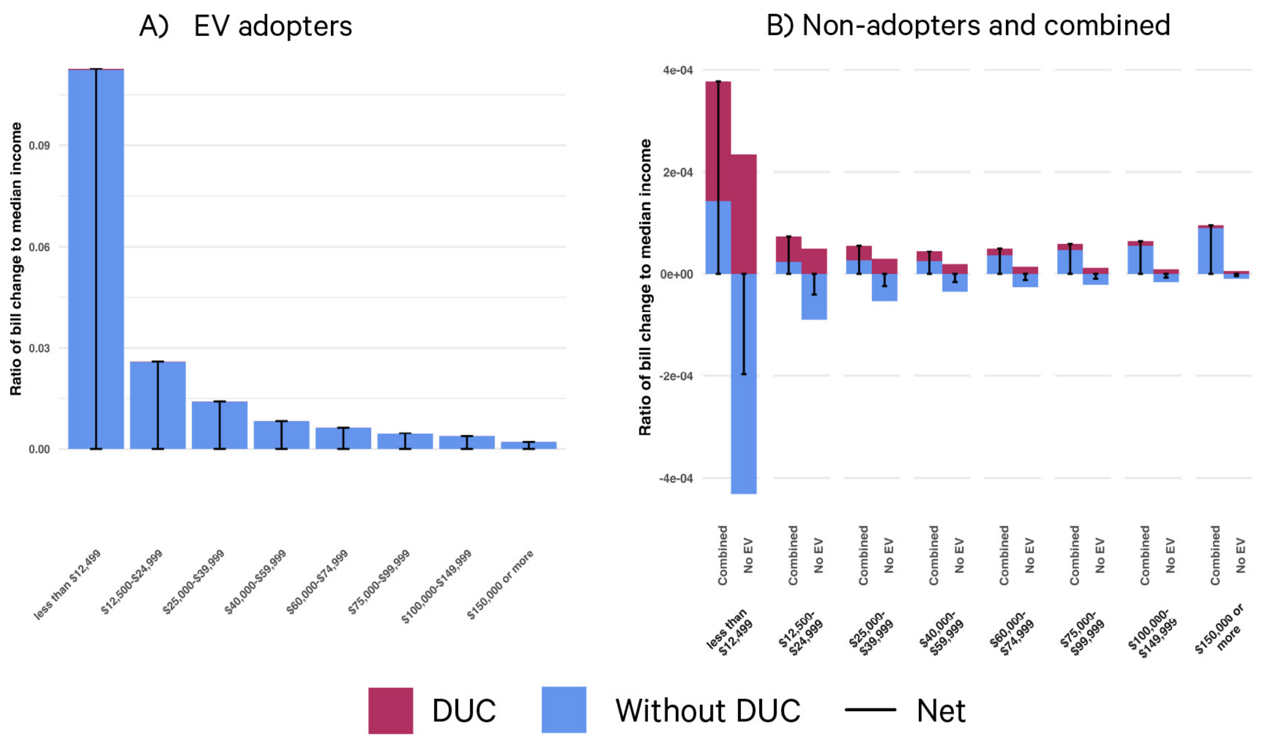

Notes: The figure shows the ratio of bill changes to median income by income group caused by rooftop solar adoption and assuming an elasticity of average price to consumption equal to −0.385. Retailers adjust fixed charges to match estimated average price changes, and they do not change variable rates. Panel A includes households that adopt solar, and Panel B includes all households ("combined") and households that do not adopt solar. The black line indicates the net ratio of bill changes to income, which can be decomposed into two components: the portion attributable to distribution upgrade costs (DUC, maroon) and the portion excluding DUC (blue).

## Figure 10. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Variable Rates



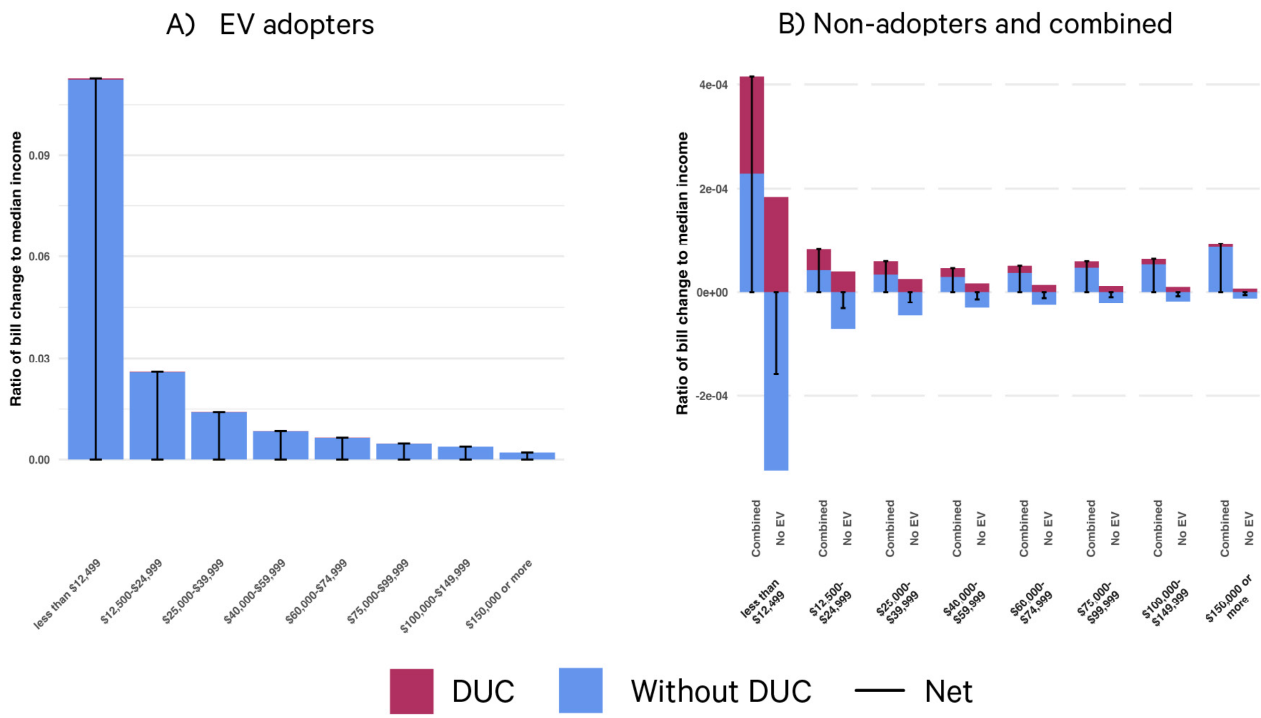

Notes: The figure shows the ratio of bill changes to median income by income group caused by rooftop solar adoption and assuming an elasticity of average price to consumption equal to −0.385. Retailers adjust variable rates to match estimated average price changes, and they do not change fixed charges. Panel A includes households that adopt solar, and Panel B includes all households ("combined") and households that do not adopt solar. The black line indicates the net ratio of bill changes to income, which can be decomposed into two components: the portion attributable to distribution upgrade costs (DUC, maroon) and the portion excluding DUC (blue).

## Figure 11. Ratio of Bill Change to Median Income: EVs with Endogenous Fixed Charges



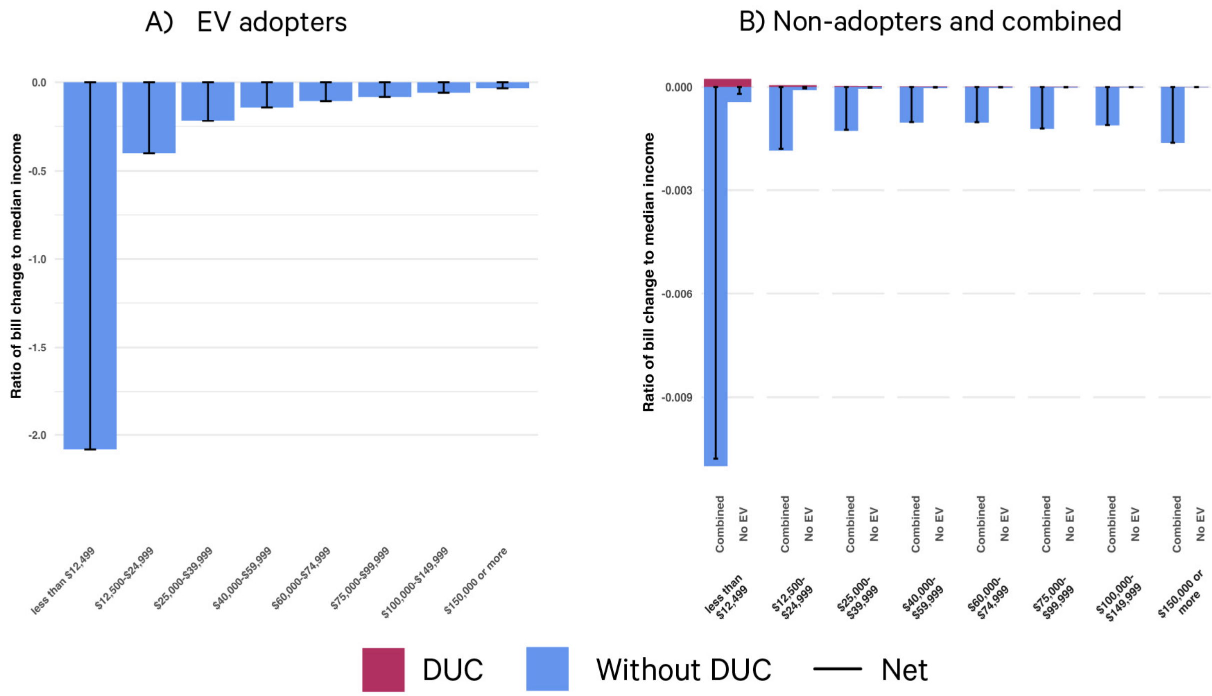

Notes: The figure shows the ratio of bill changes to median income by income group caused by EV adoption and assuming an elasticity of average price to consumption equal to −0.385. Retailers adjust fixed charges to match estimated average price changes and they do not change variable rates. Panel A includes households that adopt EVs, and Panel B includes all households ("combined") and households that do not adopt EVs. The black line indicates the net ratio of bill changes to income, which can be decomposed into two components: the portion attributable to distribution upgrade costs (DUC, maroon) and the portion excluding DUC (blue).

## Figure 12. Ratio of Bill Change to Median Income: EVs with Endogenous Variable Rates



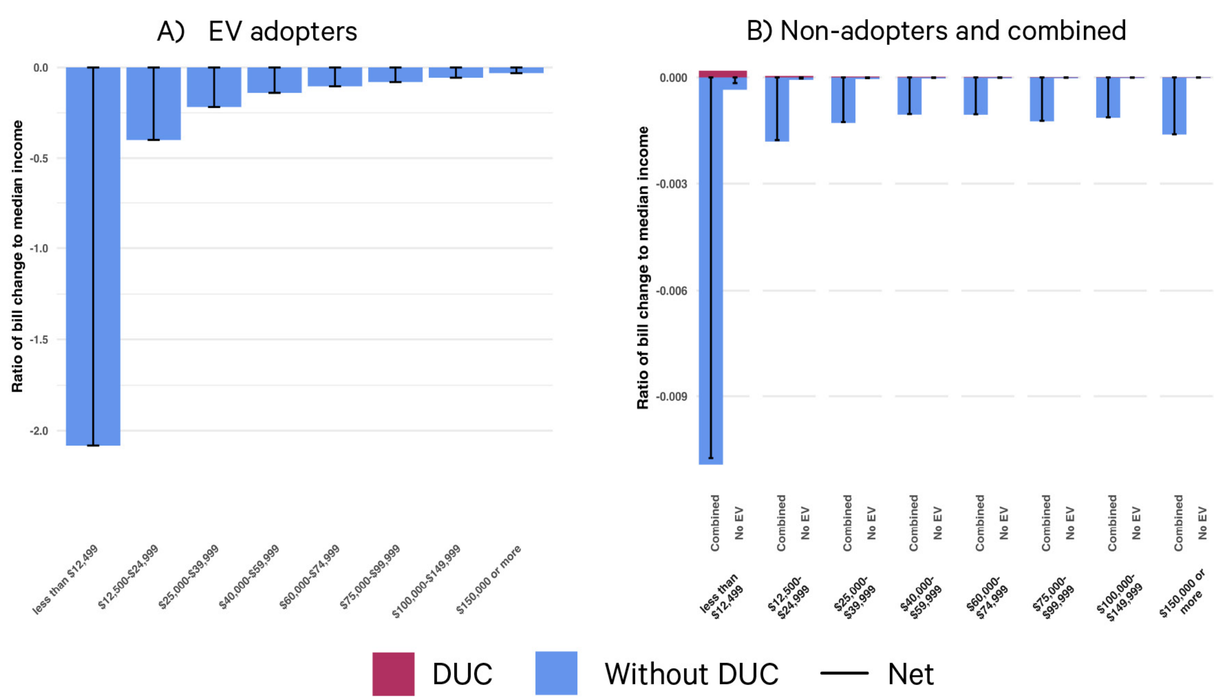

Notes: The figure shows the ratio of bill changes to median income by income group caused by EV adoption and assuming an elasticity of average price to consumption equal to −0.385. Retailers adjust variable rates to match estimated average price changes, and they do not change fixed charges. Panel A includes households that adopt EVs, and Panel B includes all households ("combined") and households that do not adopt EVs. The black line indicates the net ratio of bill changes to income, which can be decomposed into two components: the portion attributable to distribution upgrade costs (DUC, maroon) and the portion excluding DUC (blue).

## Figure 13. Ratio of Bill Change to Median Income, Including EV Subsidy: EVs with Endogenous Fixed Charges




Note: This figure is the same as Figure 11, except that it assumes a $7,500 subsidy for each EV adopter.

## Figure 14. Ratio of Bill Change to Median Income, Including EV Subsidy: EVs with Endogenous Variable Rates




Note: This figure is the same as Figure 12, except that it assumes a $7,500 subsidy for each EV adopter.

# Appendix: Calculation of distribution upgrade costs

**Solar**: Households with rooftop solar are assumed to draw zero power from the grid while remaining connected as a backup. To accommodate additional photovoltaic (PV) adoption, the grid needs to be upgraded. We calculate the distribution upgrade costs (DUC) as follows:

$$DUC = \text{average capital cost} \times \text{system size}$$

where system size is defined as:

$$\text{system size} = \text{annual energy produced by PV} / (\text{capacity factor} \times \text{total hours per year})$$

We use the National Renewable Energy Laboratory's estimate of an average capital cost of $0.07 per watt of direct current capacity (WDC) (Horowitz et al., 2018) and an average capacity factor of 15.7 percent for residential solar. To account for regional cost variation, we adjust the total distribution upgrade costs for each state using the US Army Corps of Engineers Civil Works Construction Cost Index System (CWCCIS) State Adjustment Factors. Finally, we annualize the costs using the Real Economic Carrying Charge (RECC) method, applying a 10 percent rate, consistent with the approach used in Cutter et al. (2021).

**EV**: Electric vehicle (EV) owners are assumed to drive an additional 10,000 miles per year, increasing electricity demand and requiring grid upgrades. We calculate the distribution upgrade costs (DUC) as follows:

$$DUC = \text{marginal electric utility distribution upgrade costs} \times \text{coincident charging power during the peak time},$$

where coincident charging power during the peak time is defined as:

$$\text{charging power} = \text{total number of EV} \times \text{charging power per EV} \times \text{coincidence factor}$$

Based on Cutter et al. (2021), we adopt an estimate of $400/kW (equivalent to $40/kW-Yr) for marginal electric utility distribution upgrade costs driven by EV charging. According to the Department of Transportation, Level 2 chargers operate at 7–19 kW, and we use an average of 11 kW as recommended in the same study. Under their clean drive scenario, EV charging is projected to reach a coincident peak load of 113 GW by 2035, while the total connected load of all EV chargers is expected to reach 804 GW. From these projections, we calculate a coincidence factor of approximately 0.14. To account for regional variation, we adjust the total distribution upgrade costs for each state using the US Army Corps of Engineers Civil Works Construction Cost Index System (CWCCIS) State Adjustment Factors.

# Appendix Tables and Figures

## Table A1. Full Results of Estimated Elasticity of Residential Retail Price to Residential Demand

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **First stage** | **Second stage** | **First stage** | | **Second stage** |
| | Residential sales | | Residential sales | Industrial sales | |
| Residential sales | | −0.392***<br>(0.0325) | | | −0.393***<br>(0.0359) |
| Industrial sales | | | | | 0.00993<br>(0.0173) |
| Cooling degree days | | 5.80e-06<br>(2.15e-05) | | 1.82e-05<br>(2.12e-05) | |
| Cooling degree days squared | | 3.88e-08***<br>(6.44e-09) | | 3.63e-08***<br>(6.38e-09) | |
| Heating degree days | | 8.02e-05***<br>(6.76e-06) | | 7.50e-05***<br>(6.76e-06) | |
| Heating degree days squared | | −3.00e-09***<br>(4.33e-10) | | −2.55e-09***<br>(4.35e-10) | |
| Industrial demand index | | | 0.344***<br>(0.0728) | 2.516***<br>(0.262) | |
| Weighted gas price | 0.00171<br>(0.00464) | 0.0108***<br>(0.00286) | 0.00283<br>(0.00459) | −0.0834***<br>(0.0173) | 0.0117***<br>(0.00340) |
| Constant | 10.59***<br>(0.0271) | | 9.105***<br>(0.314) | −0.962<br>(1.135) | |
| Observations | 62,278 | 62,192 | 62,278 | 62,278 | 62,192 |
| R-squared | 0.399 | 0.924 | 0.403 | 0.057 | 0.924 |
| Number of utility-states | 2,619 | 2,533 | 2,619 | 2,619 | 2,533 |
| Cragg-Donald Wald F statistic | | 246.32 | | | 119.596 |
| Hansen J statistic | | 35.260 | | | 35.644 |

### Table A2. Full Results of Estimated Elasticity of Residential Retail Price to Residential Demand

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **First stage** | | | **Second stage** |
| | Residential sales | Industrial sales | Residential sales×public | Industrial sales |
| Residential sales | | | | −0.408***<br>(0.0393) |
| Industrial sales | | | | 0.0236<br>(0.0191) |
| Residential sales×public | | | | 0.146***<br>(0.0412) |
| Cooling degree days | 2.42e–05<br>(3.26e–05) | −6.31e-05<br>(0.000144) | −0.000143***<br>(8.50e–06) | |
| Cooling degree days squared | 4.84e–08***<br>(9.45e–09) | 9.67e–08**<br>(4.01e–08) | 1.32e-08***<br>(1.65e–09) | |
| Heating degree days | 9.39e–05***<br>(7.88e-06) | 5.93e–05<br>(4.27e–05) | −4.86e–06<br>(3.10e–06) | |
| Heating degree days squared | −3.07e–09***<br>(5.60e–10) | −9.16e–10<br>(2.83e–09) | 3.95e–10**<br>(1.81e–10) | |
| Industrial demand index | 0.207*<br>(0.109) | 2.863***<br>(0.474) | 0.358***<br>(0.0459) | |
| Cooling×public | 4.15e–05<br>(3.48e–05) | −1.15e–05<br>(0.000154) | 0.000373***<br>(2.02e–05) | |
| Cooling sq×public | −2.71e–05***<br>(9.92e–06) | 5.21e-05<br>(4.68e–05) | 8.18e–05***<br>(7.91e–06) | |
| Heating×public | −4.01e–08***<br>(1.07e-08) | −1.25e–07***<br>(4.47e–08) | −1.88e–08***<br>(6.95e–09) | |
| Heating sq×public | 7.01e–10<br>(7.76e–10) | -4.71e–09<br>(3.49e–09) | −3.94e–09***<br>(5.98e–10) | |
| Ind demand×public | 0.179<br>(0.117) | −0.627<br>(0.488) | −0.813***<br>(0.0549) | |
| Weighted gas price | 0.00227<br>(0.00403) | −0.0799***<br>(0.0175) | −0.00194<br>(0.00273) | 0.0131***<br>(0.00349) |
| Constant | 9.127***<br>(0.261) | −0.733<br>(1.157) | 6.154***<br>(0.179) | |
| Observations | 59,694 | 59,694 | 59,694 | 59,611 |
| R-squared | 0.428 | 0.058 | 0.343 | 0.927 |
| Number of utility-states | 2,506 | 2,506 | 2,506 | 2,506 |

Notes: Column and row headings with "×public" indicate that the variable is interacted with a dummy for a public utility. Standard errors in parentheses, clustered by utility. *** p<0.01, ** p<0.05, * p<0.1.

**Table A3. Full Results of Estimated Elasticity of Residential Retail Price to Residential Demand**

| | (1) | (2) | (3) |
|---|---|---|---|
| | **First stage** | **First stage** | **Second stage** |
| | Residential sales | Industrial sales | |
| Residential sales | | | -0.427*** (0.0496) |
| Industrial sales | | | 0.0274 (0.0227) |
| Cooling degree days | 6.94e–05*** (2.27e–05) | –4.32e–05 (9.76e–05) | |
| Cooling degree days squared | 2.26e–08*** (7.38e–09) | 2.40e–08 (3.10e–08) | |
| Heating degree days | 9.85e–05*** (8.40e–06) | 0.000116*** (3.74e–05) | |
| Heating degree days squared | –4.02e–09*** (6.06e–10) | –7.39e–09*** (2.48e–09) | |
| Industrial demand index | 0.426*** (0.0791) | 2.558*** (0.315) | |
| Weighted gas price | –0.000696 (0.00532) | –0.0480*** (0.0183) | 0.00545 (0.00404) |
| Constant | 18.68*** (0.0592) | 9.819*** (0.266) | |
| Observations | 32,423 | 32,423 | 32,418 |
| R-squared | 0.546 | 0.106 | 0.931 |
| Number of utility-states | 1,066 | 1,066 | 1,061 |
| Cragg-Donald Wald F statistic | | | 73.025 |
| Hansen J statistic | | | 28.117 |

Notes: Standard errors in parentheses, clustered by utility. *** p<0.01, ** p<0.05, * p<0.1

## Table A4. Estimated Elasticity of Residential Retail Price to Residential Demand Including All Weather Covariates

| | (1) | (2) | (3) |
|---|---|---|---|
| | First stage | First stage | Second stage |
| Residential sales | | | −0.363***<br>(0.0522) |
| Industrial sales | | | 0.00391<br>(0.0162) |
| Cooling degree days_East | 6.89e−06<br>(2.24e−05) | −8.72e−05<br>(8.66e−05) | |
| Cooling degree days_West | 0.000144*<br>(7.45−-05) | 0.000291<br>(0.000283) | |
| Cooling degree days squared_East | 2.64e−08***<br>(7.06e−09) | 2.78e−08<br>(2.63e−08) | |
| Cooling degree days squared_West | 5.61e−08*<br>(3.30e−08) | −1.05e−07<br>(9.97e−08) | |
| Heating degree days_East | 8.14e−05***<br>(6.84e−06) | 8.49e−05***<br>(3.08e−05) | |
| Heating degree days_West | −4.87e−05<br>(3.46e−05) | −9.94e−05<br>(0.000222) | |
| Heating degree days squared_East | −2.69e−09***<br>(4.90e−10) | −3.14e−09<br>(2.11e−09) | |
| Heating degree days squared_West | 4.80e−09**<br>(2.43e−09) | 9.95e−09<br>(1.50e−08) | |
| Extreme cooling degree days | 0.0353***<br>(0.0111) | 0.0291<br>(0.0405) | |
| Extreme heating degree days | 0.00322<br>(0.00584) | −0.0147<br>(0.0240) | |
| Industrial demand index | 0.329***<br>(0.0717) | 2.501***<br>(0.260) | |
| Weighted gas price | 0.00283<br>(0.00459) | −0.0824***<br>(0.0172) | 0.0111***<br>(0.00319) |
| Constant | 9.213***<br>(0.308) | −0.850<br>(1.124) | |
| Observations | 62,278 | 62,278 | 62,192 |
| R-squared | 0.402 | 0.057 | 0.763 |
| Number of utility-states | 2,619 | 2,619 | 2,533 |
| Cragg-Donald Wald F statistic | | | 53.867 |
| Hansen J statistic | | | 59.789 |

Notes: Standard errors are in parentheses, clustered by utility. Observations are at utility-state-year level and are weighted by the utility's average number of residential customers. The dependent variable is the log of the average price; residential and industrial sales are in logs. Columns 1 and 2 report the first stages for residential and industrial sales, and column 3 reports the second stage. Besides the reported variables, all regressions include utility-state and year fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

**Figure A1. Scatter Plot of Predicted Residential Sales and Actual Values**

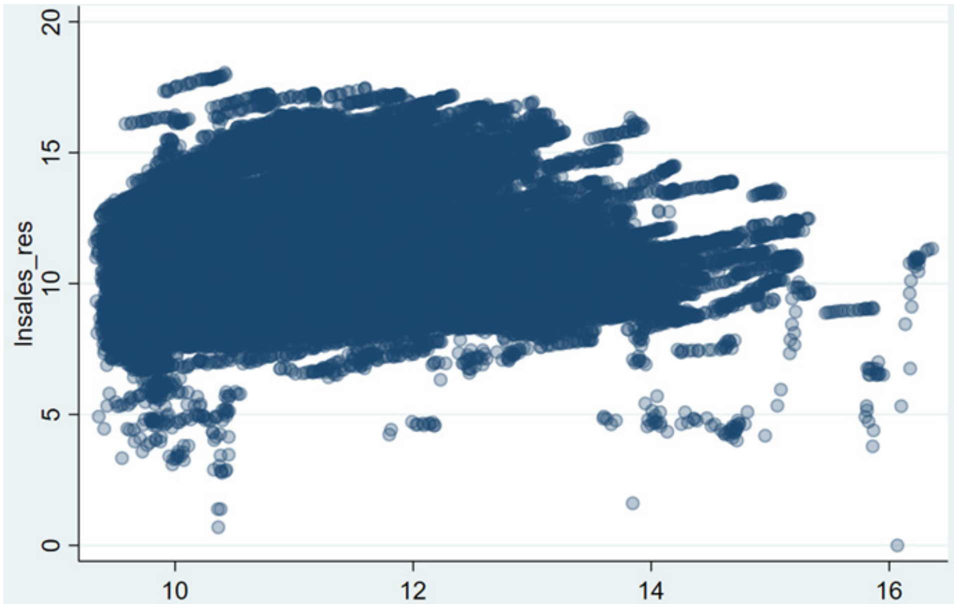
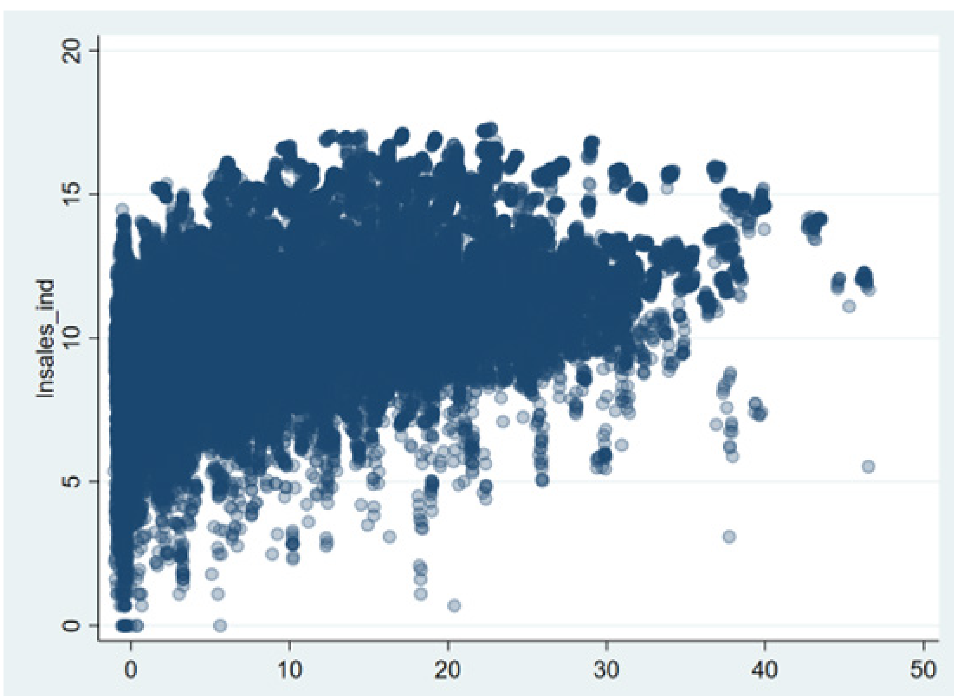
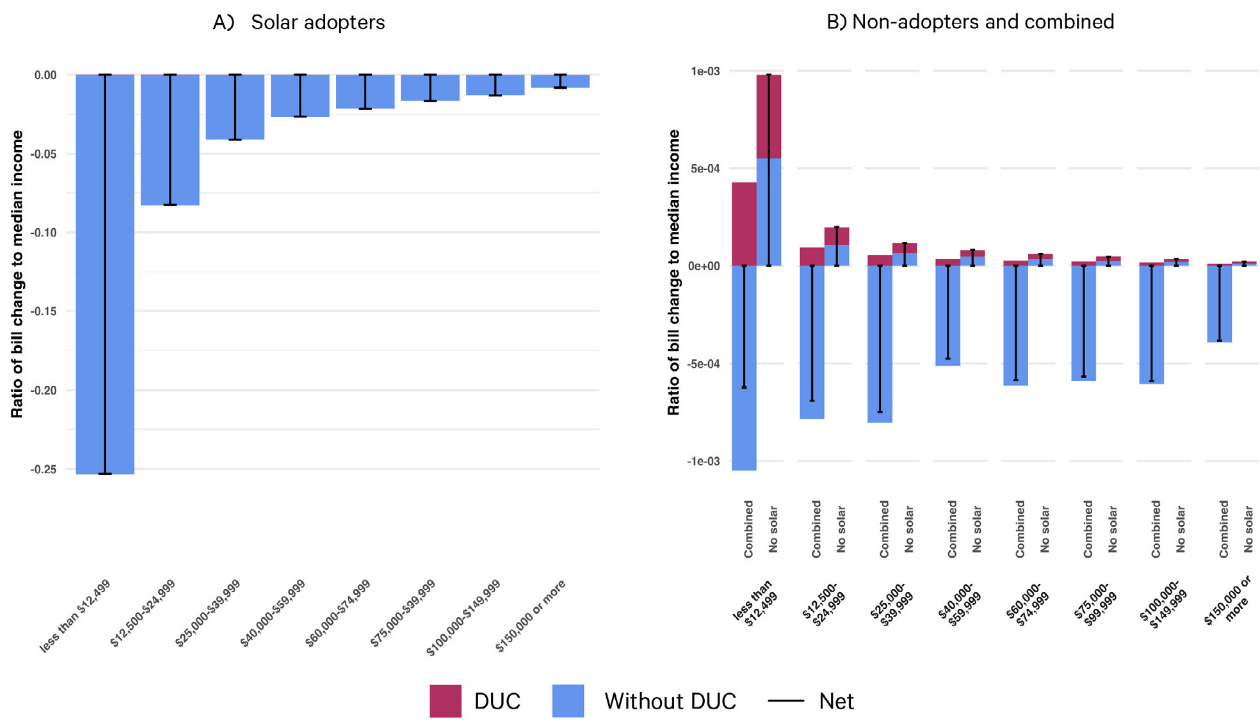



**Figure A2. Scatter Plot of Predicted Industrial Sales and Actual Values**

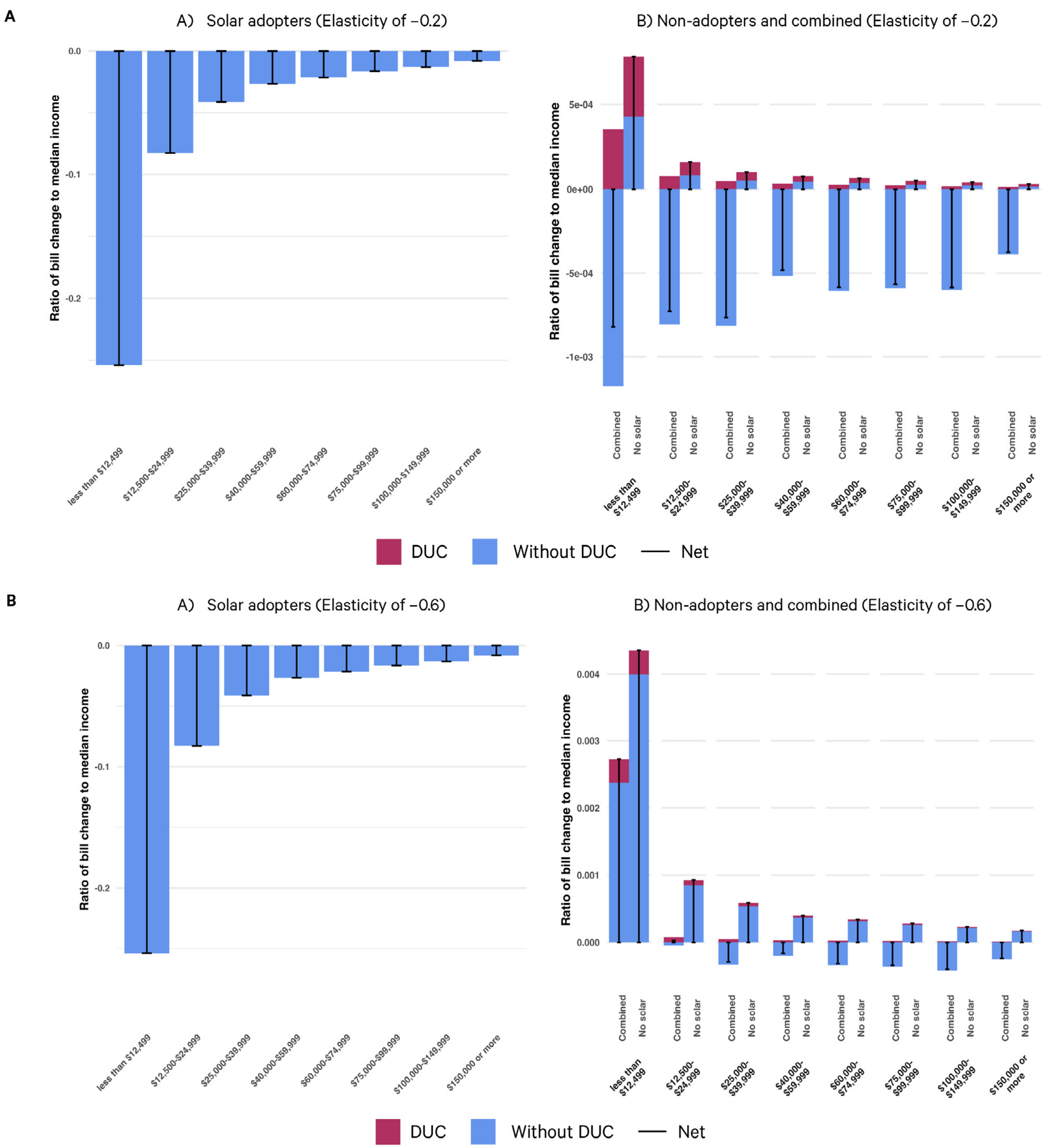


## Figure A3. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Fixed Charges and Elasticity of −0.2



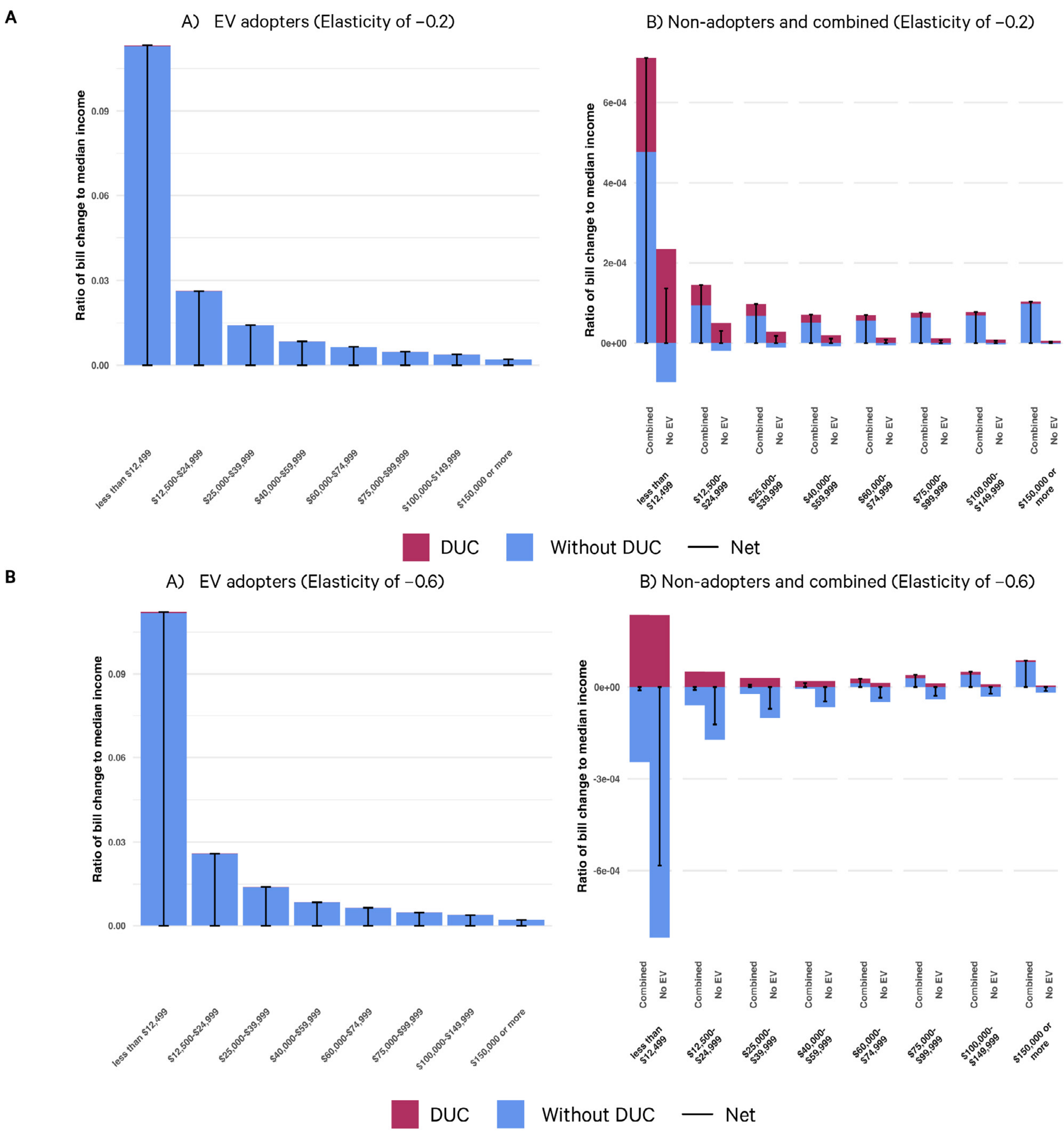

Note: This figure is the same as Figure 9, except that it includes an elasticity of average price with respect to demand of −0.2 instead of −0.385.

## Figure A4. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Variable Rates and Elasticity of −0.2 and −0.6



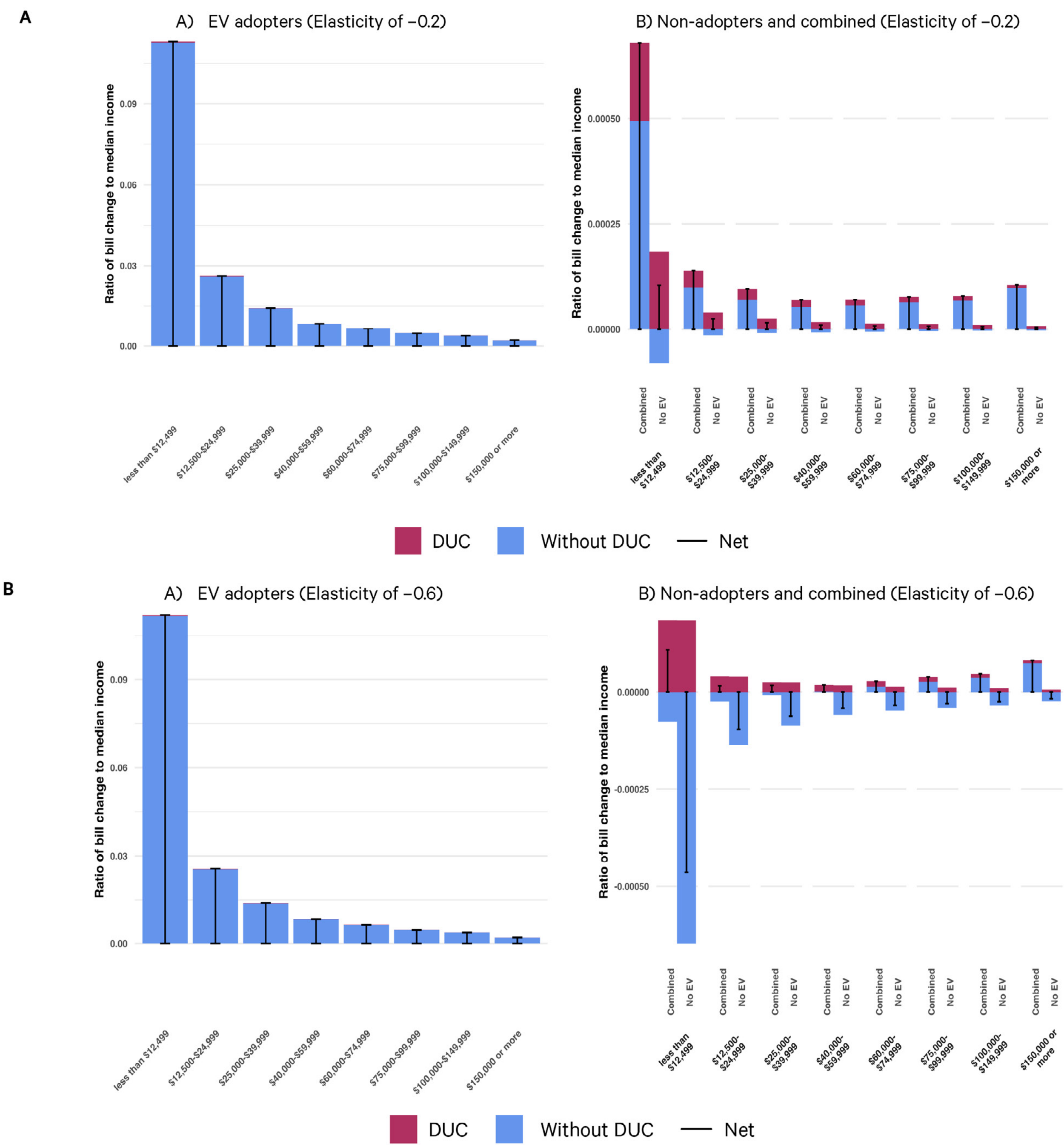

Note: This figure is the same as Figure 10, except that it includes an elasticity of average price with respect to demand of −0.2 and −0.6 instead of −0.385.

## Figure A5. Ratio of Bill Change to Median Income: EVs with Endogenous Fixed Charges and Elasticity of −0.2 and −0.6



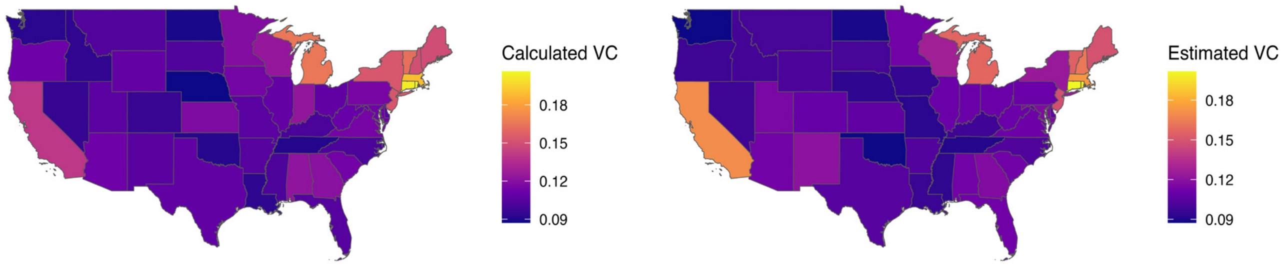

Note: This figure is the same as Figure 11, except that it includes an elasticity of average price with respect to demand of −0.2 and −0.6 instead of −0.385.

## Figure A6. Ratio of Bill Change to Median Income: EVs with Endogenous Variable Rates and Elasticity of −0.2 and −0.6



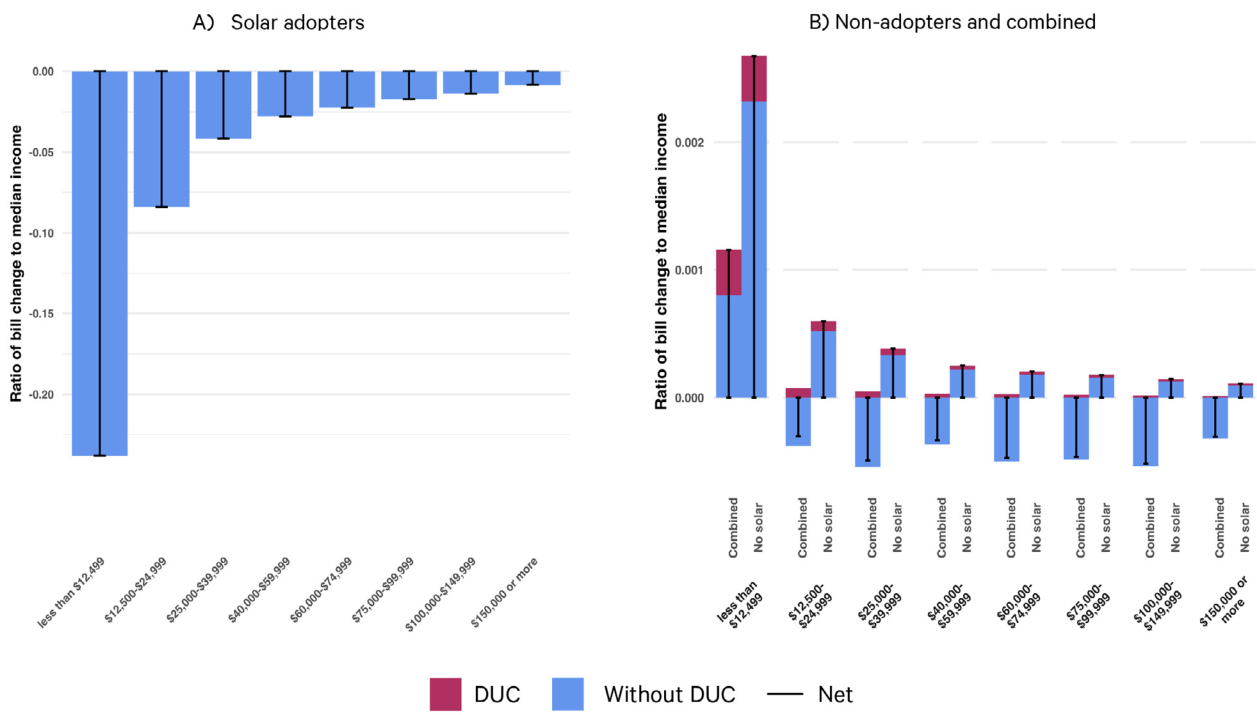

Note: This figure is the same as Figure 12, except that it includes an elasticity of average price with respect to demand of −0.2 and −0.6 instead of −0.385.

## Figure A7. Calculated and Estimated Variable Charges Across States



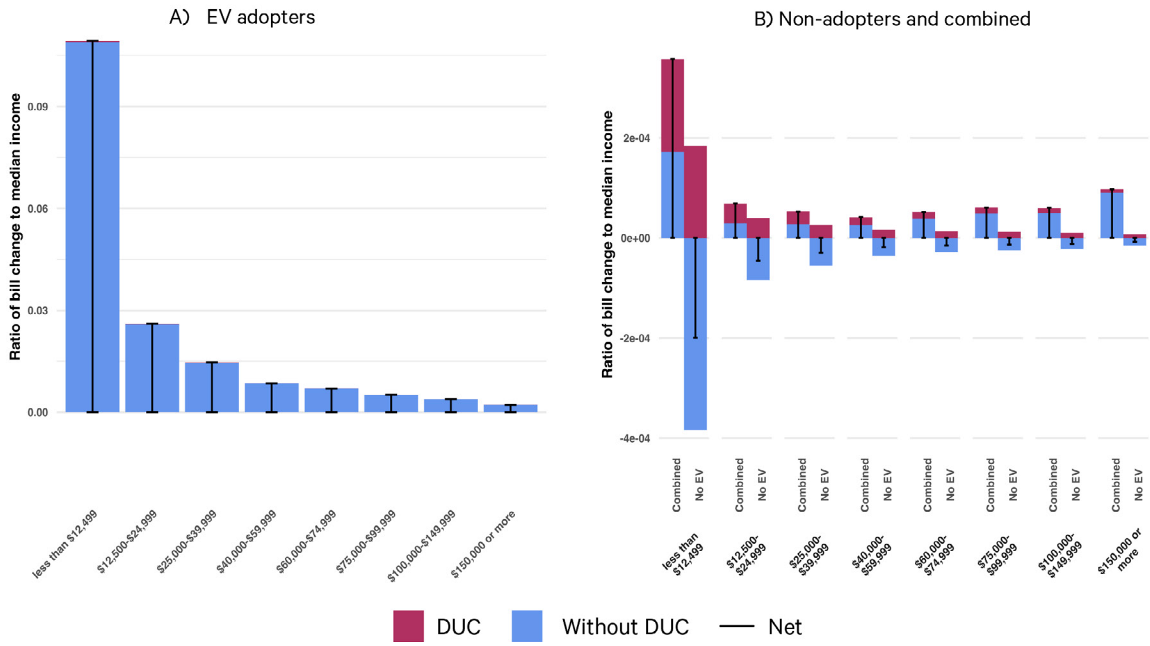

Note: The figure maps variable electricity charges across the contiguous US states. Alaska and Hawaii are excluded for visualization purposes but included in the analysis. Variable charges are measured in dollars per kilowatt-hour ($/kWh). The left panel shows calculated charges based on utility tariff data from the OpenEI Utility Rate Database, while the right panel presents estimated charges derived from state-level regressions of household electricity expenditures on consumption.

## Figure A8. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Variable Rates



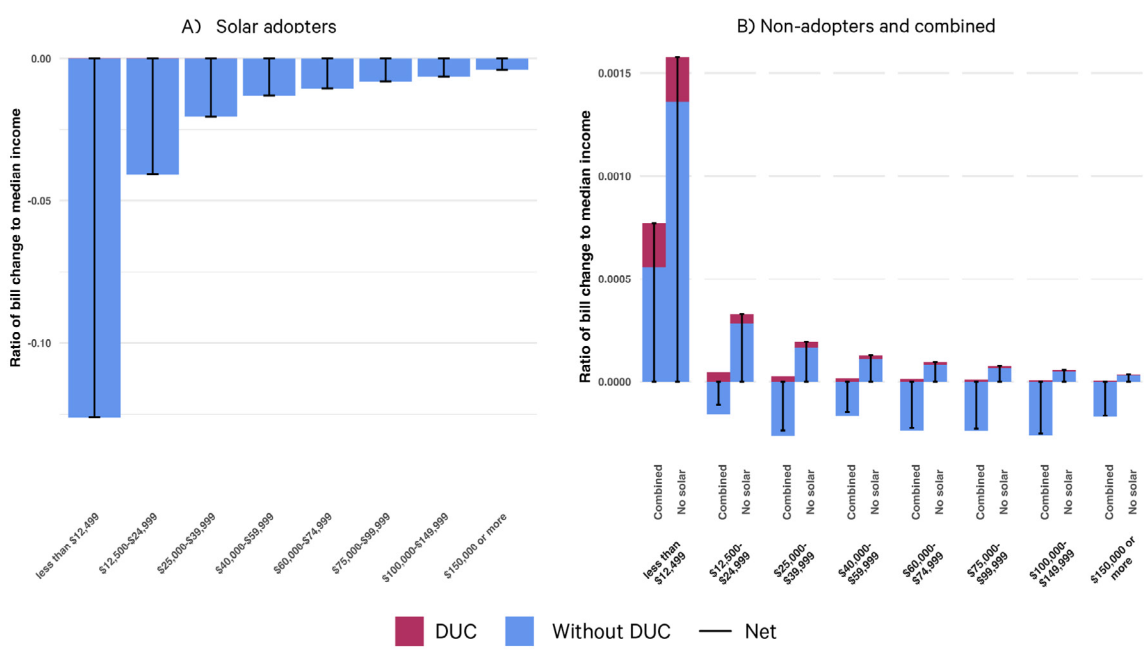

Note: This figure is the same as Figure 10, except that it uses regression-estimated variable costs.

## Figure A9. Ratio of Bill Change to Median Income: EVs with Endogenous Variable Rates



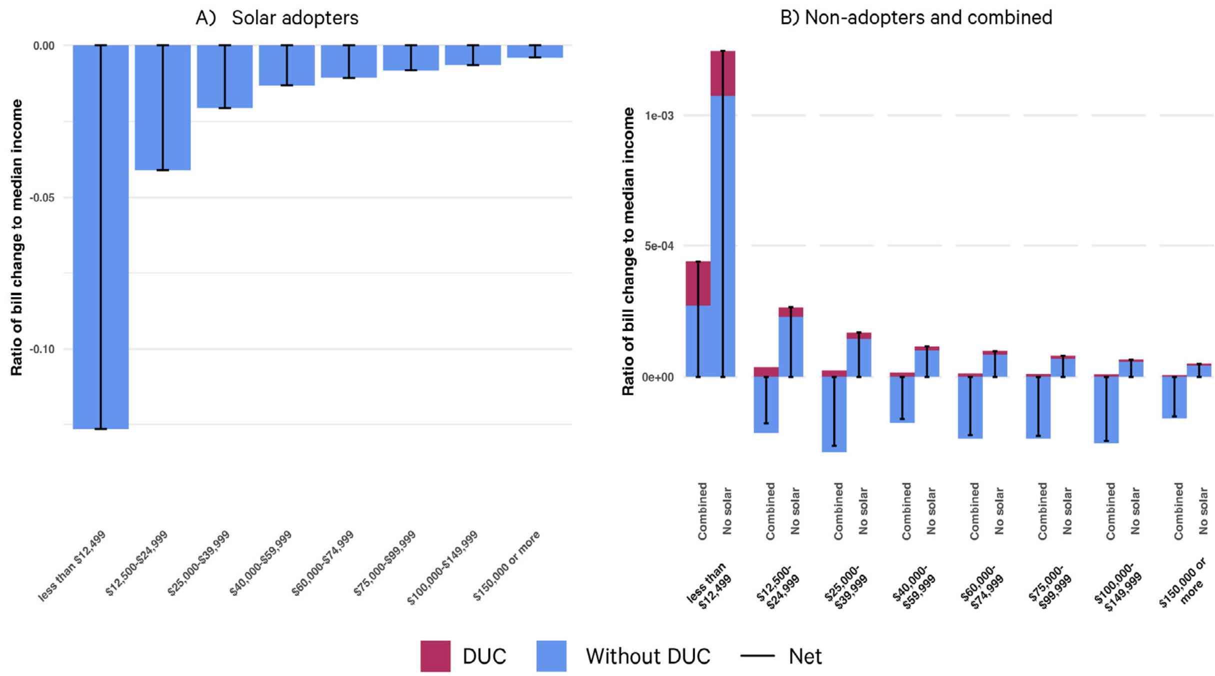

Note: This figure is the same as Figure 12, except that it uses regression-estimated variable costs.

## Figure A10. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Fixed Charges



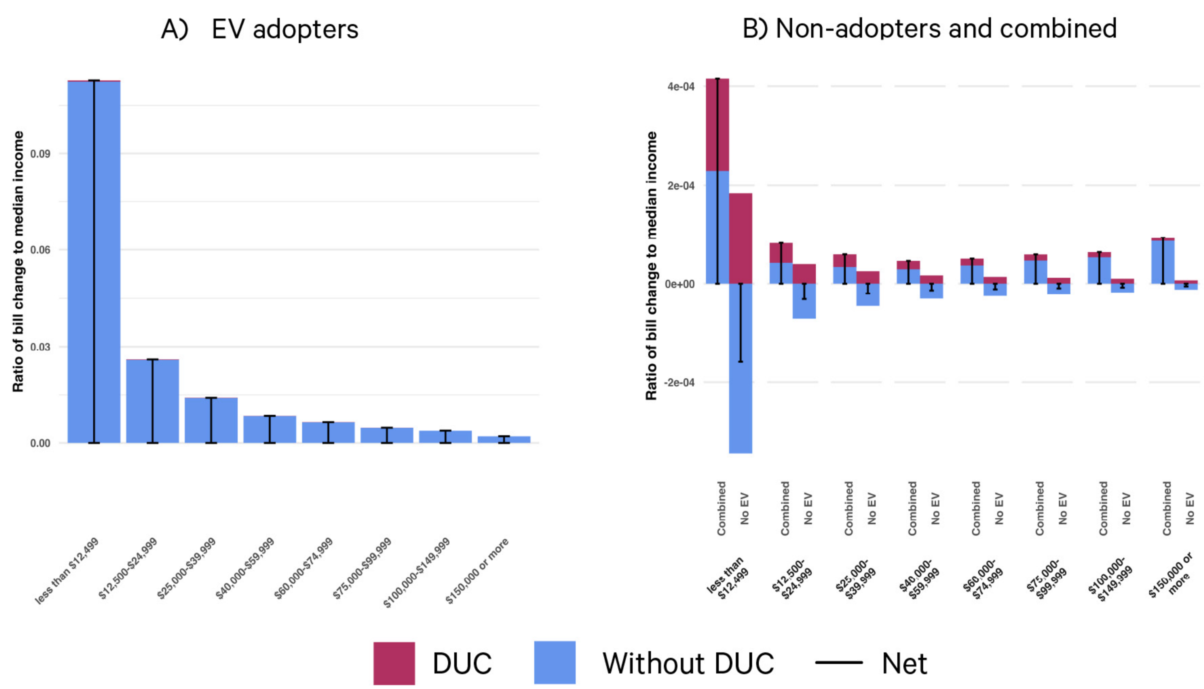

Note: This figure is the same as Figure 9, except it assumes rooftop solar offsets 50 percent of consumption instead of fully displacing grid consumption for adopters.

## Figure A11. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Variable Rates



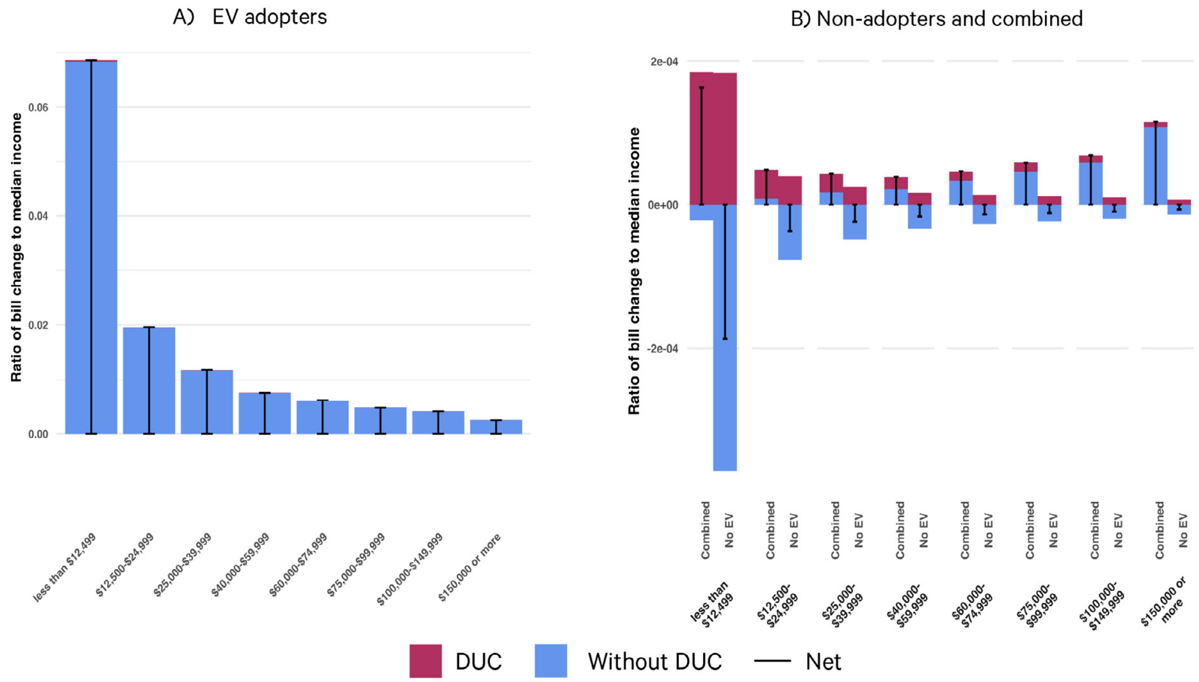

Note: This figure is the same as Figure 10, except it assumes rooftop solar offsets 50 percent of consumption instead of fully displacing grid consumption for adopters.

## Figure A12. Ratio of Bill Change to Median Income: EVs with Endogenous Fixed Charges



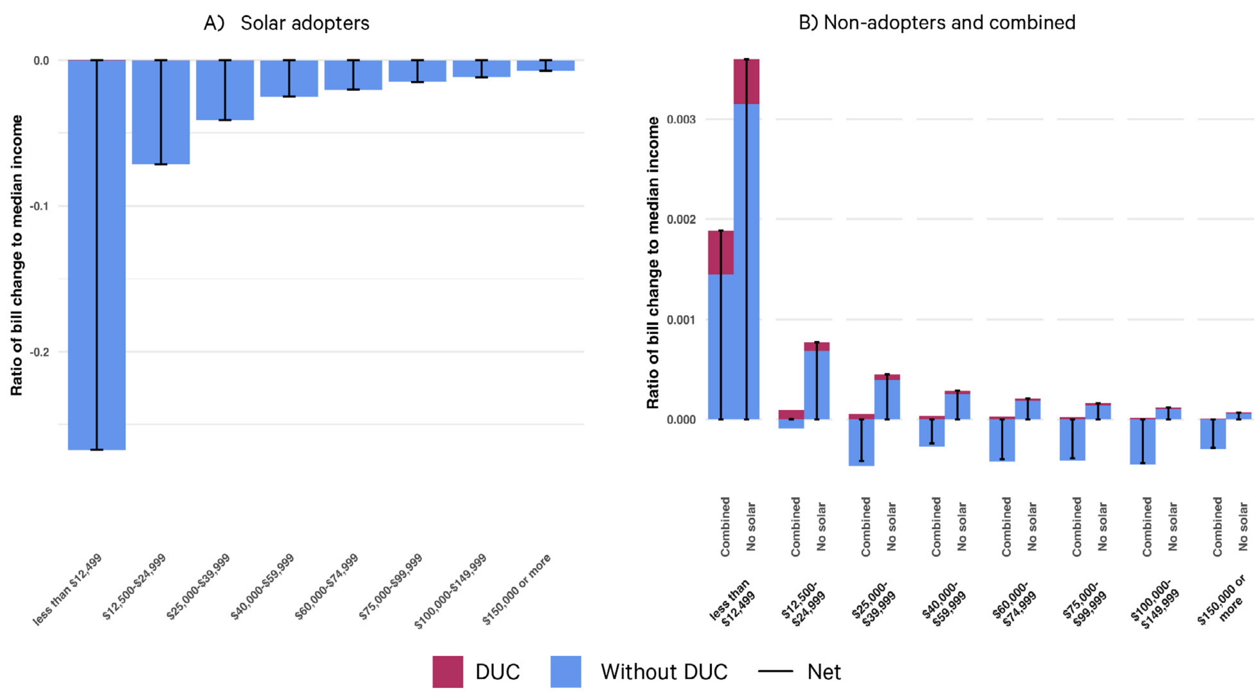

Note: This figure is the same as Figure 11, except that it assumes vehicle miles traveled (VMT) vary by income group.

## Figure A13. Ratio of Bill Change to Median Income: EVs with Endogenous Variable Rates



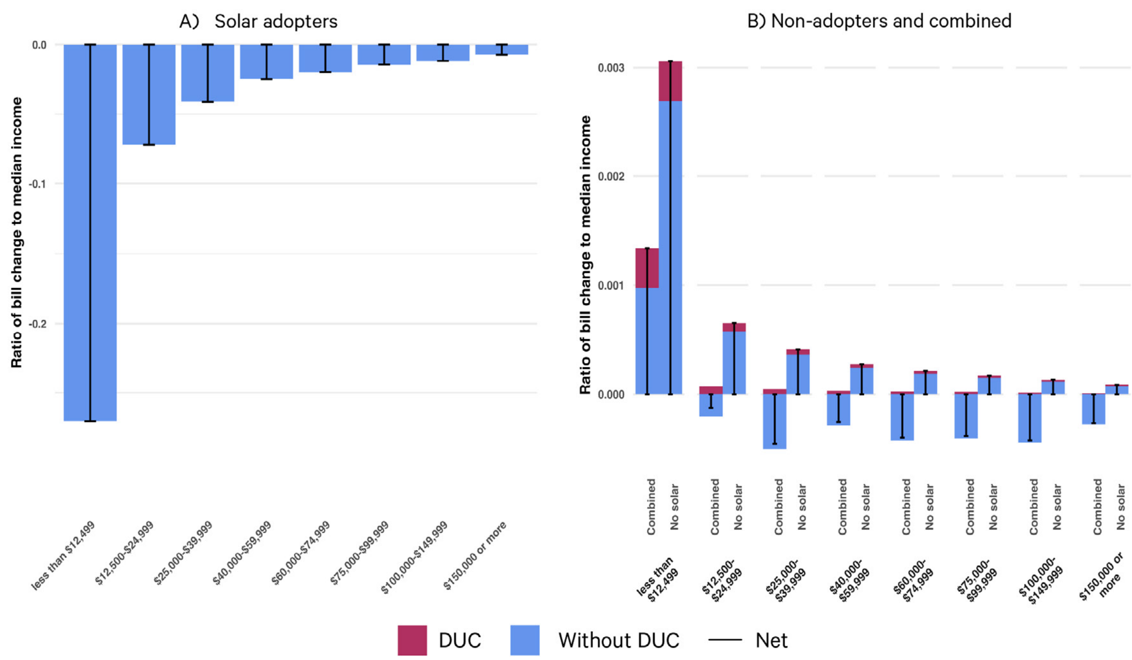

Note: This figure is the same as Figure 12, except that it assumes vehicle miles traveled (VMT) vary by income group.

## Figure A14. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Fixed Charges



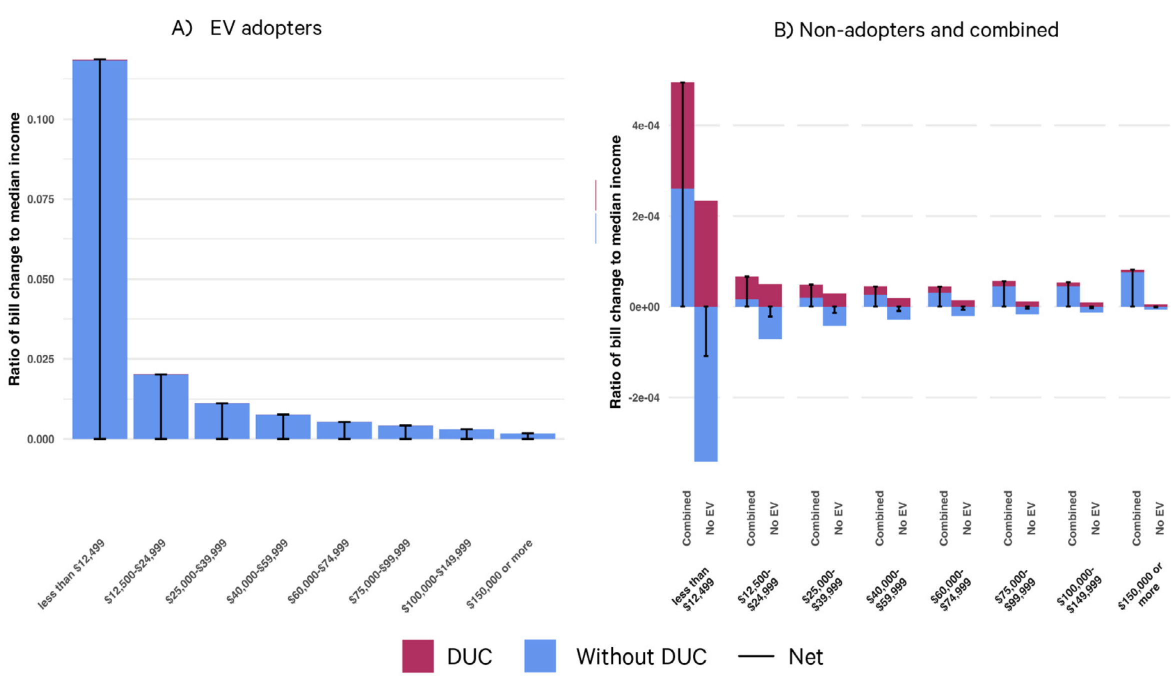

Note: This figure is the same as Figure 9, except that it assumes a single national utility in which all households face the same national average electricity prices, and it uses a structural estimate of price elasticity equal to −0.4.

## Figure A15. Ratio of Bill Change to Median Income: Rooftop Solar with Endogenous Variable Rates



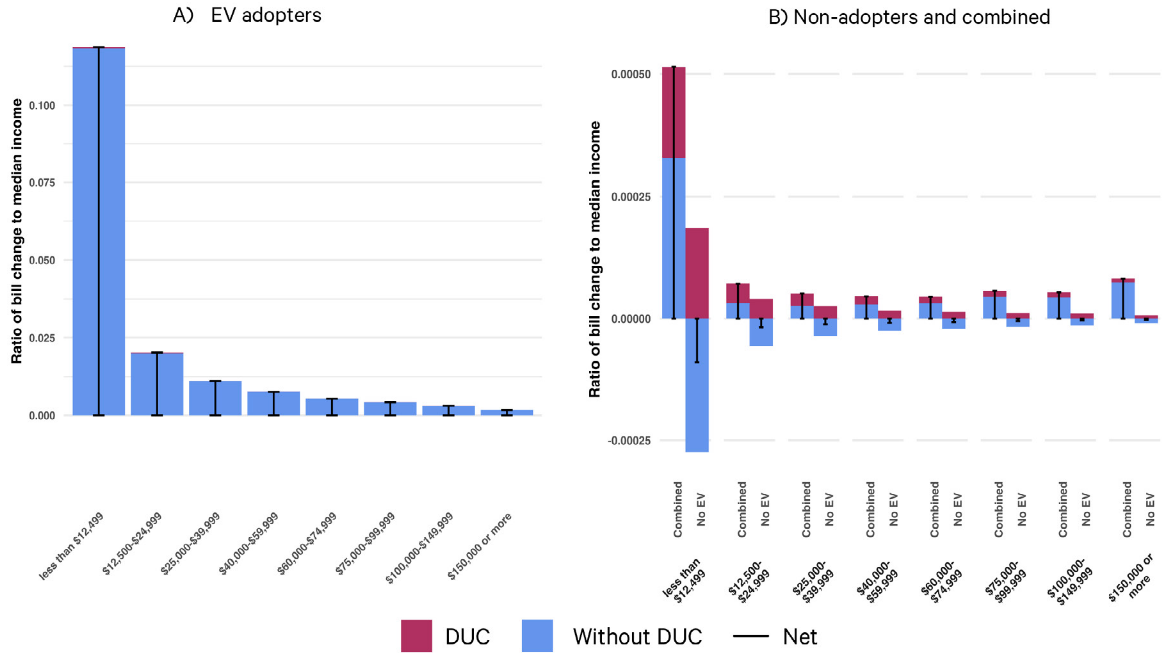

Note: This figure is the same as Figure 10, except that it assumes a single national utility in which all households face the same national average electricity prices, and it uses a structural estimate of price elasticity equal to −0.4.

## Figure A16. Ratio of Bill Change to Median Income: EVs with Endogenous Fixed Charges




Note: This figure is the same as Figure 11, except that it assumes a single national utility in which all households face the same national average electricity prices, and it uses a structural estimate of price elasticity equal to −0.4.

## Figure A17. Ratio of Bill Change to Median Income: EVs with Endogenous Variable Rates




Note: This figure is the same as Figure 12, except that it assumes a single national utility in which all households face the same national average electricity prices, and it uses a structural estimate of price elasticity equal to −0.4.