Homework in Climate Economics: Household Production, Environmental Preferences, and Climate Policy

Stephie Fried — FRB San Francisco and CEPR

David Lagakos — BU and NBER

Hannah Rhodenhiser — BU

February 20, 2025

Abstract

This paper studies emissions from household energy use, which account for one third of U.S. emissions. We draw on a new survey to document that some households purchase energy-saving equipment because, in addition to cutting energy costs, they want to reduce emissions. We build a macro-environmental model in which emissions result from home production tasks involving either clean or dirty equipment, and some households have distaste for their own emissions. We analyze the most cost-effective subsidy on clean equipment. We show that changes in households' emissions distaste have similar effects on household emissions as a modest sized carbon tax.

JEL Codes: Q54; E23; H23

Keywords: Climate change; Home production; Environmental macroeconomics

Email: stephie.fried@sf.frb.org, lagakos@bu.edu, hmrh@bu.edu.

The views expressed in this paper are our own and do not reflect the views of the Federal Reserve System or its staff. For helpful comments and suggestions we thank seminar participants at the Boston Fed, BU, the Bank of Spain, the European Commission, IE University, the University of Kentucky, the World Bank IMF Joint Seminar, the CEPR Climate Change and the Environment Conference Paris, and the ETH Workshop on Climate Change and Economic Policy, as well as Mark Bils, Moritz Kuhn, Pete Klenow, Elizabeth Mattiuzzi, Fernanda Nechio, Lydia Petersen, Myroslav Pidkuyko, Brigitte Roth Tran, Kerry Smith, Thomas Storek, and Stephen Terry. All potential errors are our own.

1. Introduction

Emissions from household activities, such as driving and heating, account for approximately one third of U.S. emissions. Reducing these emissions has been an important focus of federal and state climate policy. For example, the U.S. Inflation Reduction Act (IRA) budgeted around $60 billion in subsidies for purchases of electric cars, solar panels, and other clean equipment to raise energy efficiency in home production (see e.g. Bistline, Mehrotra and Wolfram, 2023). Likewise, over half of U.S. states have additional incentive programs to increase residential energy efficiency.[1] Yet, the macroeconomic literature studying the effects of climate policy has largely abstracted from home production, focusing instead on firm production (e.g. Golosov, Hassler, Krusell and Tsyvinski, 2014; Barrage and Nordhaus, 2024), innovation (e.g., Acemoglu, Aghion, Bursztyn and Hémous, 2012) or the spatial reallocation of economic activity (e.g., Cruz and Rossi-Hansberg, 2024).

This paper develops a model of home production and household energy use to study the determinants of household carbon emissions and how they respond to climate policy. To guide our modeling choices, we conduct a new nationally representative survey about the reasons households use (or do not use) clean equipment for different home production tasks. The conventional wisdom is that households use clean equipment whenever it makes financial sense based on energy savings, tax credits, or other monetary incentives. However, we document that a significant fraction of U.S. households use clean equipment because they care about reducing their own carbon emissions in addition to lowering their energy bills, a characteristic we refer to as environmental preference. The notion that environmental preferences can impact households' decisions builds on earlier work that studies the role of environmental preferences for firm product innovation (Aghion, Bénabou, Martin and Roulet, 2023) and for the provision of environmental public goods (Costello and Kotchen, 2022; Chan, 2024; Wichman, 2016).

With these motivations in mind, we adapt a standard model of home production (Becker, 1965; Benhabib, Rogerson and Wright, 1991) to focus on households' equipment choices and their implications for energy use and emissions. Drawing from the literature on automation (Acemoglu and Restrepo, 2019), we model home production as a continuum of home-services tasks. Households can produce each task using either dirty equipment and energy or clean equipment and no energy. The tasks are meant to capture, for example, how home lighting can be done with either incandescent or LED bulbs, and transportation can be done with either an electric or gasoline car. The relative productivity of clean equipment varies across tasks. In addition to switching to clean equipment, households can also reduce their emissions by using residential solar to directly produce clean energy.

[1] See Stock (2019) for an engaging overview of U.S. climate policy, and `www.naseo.org/sreeps` for specifics on residential energy efficiency programs by state.

Households in our model differ in their income potential and environmental preferences. We model environmental preferences as household distaste for their own emissions, similar to the warm glow of Andreoni (1990). Households with zero distaste for carbon emissions look like standard households in macroeconomic models. Households with non-zero distaste receive an environmental warm glow from reducing their emissions. Utility is non-homothetic with curvature in market consumption and home production and linear distaste for emissions.

Despite its simplicity, our model matches the key relationships from our survey between household clean equipment, environmental preferences, and income. For example, we find in our survey that clean equipment ownership is positively correlated with income, but that environmental preferences are uncorrelated with income. Our model replicates these same patterns. Reducing emissions in our model is a normal good; high-income households implicitly purchase more emissions reduction by using clean equipment for more tasks. This result does not require high-income households to have stronger environmental preferences. Instead, the mechanism comes from the non-homothecitity in utility; the relative utility benefit of a dollar spent on emissions reduction through the purchase of clean equipment increases with income, implying that high-income households use clean equipment for more tasks, all else constant.

We calibrate our model using data from our survey and from existing data sets on household equipment and energy use, including the Residential Energy Consumption Survey (RECS) and the Consumer Expenditure Survey (CEX). Our specification of utility departs from the typical approach in the home-production and environmental-macro literatures in that it includes home-services tasks and carbon emissions. As such, it is important to ensure that our model can quantitatively replicate standard features of the data such as the price elasticity of energy demand, average energy and equipment budget shares and any variation in these shares with household income. Our calibrated model matches these moments quite closely. Moreover, we show that environmental preferences are necessary to capture the heterogeneity in clean equipment use across households that we observe in the data.

We use the model to study the impact of climate subsidies directed specifically to households, such as the subsidies for electric vehicles, heat pumps, and solar panels provided by the federal government and also by state and local programs. Policymakers have two primary considerations in their design of household climate policy: (1) determining which equipment to subsidize, and (2) identifying which income groups are eligible to receive the subsidy. We solve for the subsidy policy that minimizes the cost of achieving an emissions target when the policymaker can choose both of these margins. We finance the subsidy with a flat tax on labor income.

This exercise yields two key insights for the design of cost-effective household subsidies. First, the subsidies only apply to clean equipment with intermediate levels of adoption. Subsidizing only an intermediate range of clean equipment means that the subsidy does not apply to clean equipment that most households already own, like LED lights. Nor does it apply to clean equipment that virtually no one owns in equilibrium, like dynamic windows, since the productivity of that equipment must still be too low to make the subsidies worthwhile. Instead, it applies to clean equipment like electric vehicles and heat pumps, that some, but not all, households already own.

Second, the highest income households are not eligible for the subsidies. Environmental preferences create a trade off in determining whether high-income households should be eligible. High-income households with weak environmental preferences are the biggest emitters because they produce the most home production and use relatively little clean equipment. Excluding these households requires the policymaker to use a larger subsidy to attain the emissions target, pushing the policy cost up. Working in the other direction, high-income households with strong environmental preferences are the least cost effective, in that they have the smallest emissions reduction per dollar of subsidy receipts. These households are largely inframarginal because the subsidy applies to more clean equipment that they would have bought anyway, reducing its cost-effectiveness. Excluding the highest income households from the subsidy balances the benefits from subsidizing the biggest emitters (high-income households with weak environmental preferences) with the costs from subsidizing the least cost-effective households (high-income households with strong environmental preferences).

We next use the model to gauge the impact of changes in household attitudes towards climate change on aggregate household emissions. Over the past decade, the American public has generally become more concerned about climate change (Leiserowitz et al., 2023). This trend could be due to changes in information, experiences, or beliefs, all of which would manifest as a change in environmental preferences in our model. We simulate the effect on household emissions if climate concern continues to rise over the next ten years, following the historical trend. We find that the elevated future levels of climate concern lead to a 5.2 percent reduction in aggregate household emissions, absent any climate policy. This decrease in emissions is equivalent to what policymakers could achieve with a 5.4 percent subsidy to all clean equipment, or with a 57 dollar per ton carbon tax. These results highlight that changes in household attitudes can have meaningful impacts on U.S. emissions.[2]

Related literature. This paper takes its inspiration – and title – from the literature on home production in macroeconomics, including studies of business cycles (Benhabib, Rogerson and Wright, 1991; Greenwood, Rogerson and Wright, 1993; McGrattan, Rogerson and Wright, 1997), labor supply (Rupert, Rogerson and Wright, 2000; Greenwood, Seshadri and Yorukoglu, 2005), taxa-

[2]Prior work has studied changes in preferences in other contexts, particularly for risk (see e.g., Levin and Vidart, 2023; Malmendier and Nagel, 2011; Guiso et al., 2018; Howden et al., 2022).

tion (Rogerson, 2008; Olovsson, 2015), housing (Aruoba, Davis and Wright, 2016), and inequality within (Boerma and Karabarbounis, 2021) and across countries (Parente, Rogerson and Wright, 2000). Our study departs from this literature in its focus on carbon emissions and climate policy, as well as on the prominent role we give to environmental preferences. Kuhn and Schlattmann (2024) also model households' equipment choices; they study climate policy when households can choose between an old durable good that produces carbon emissions and a modern one that does not. One key difference is they find that subsidies should target high-income households, whereas in our context this is not necessarily the case. Other previous studies have modeled household energy choices (Fried, Novan and Peterman, 2018, 2024; Känzig, 2024), but they abstract from the potential for households to use clean equipment and residential solar, a main focus of this paper and of U.S. climate policy.

A primary goal of our paper is to develop a model of home production and energy use which we can use to analyze the impact of climate subsidies targeted to households. This approach complements an empirical microeconomic literature that studies the effects of specific subsidy policies for household clean equipment, such as subsidies for energy-efficiency improvements in appliances (Davis et al., 2014) and lighting (Shojaeddini and Gilbert, 2023), as well as subsidies for electric vehicles (Muehlegger and Rapson, 2022) and weatherization upgrades (Fowlie et al., 2018; Graff Zivin and Novan, 2016). As in our analysis, these papers find that the subsidies increase uptake of the clean equipment and reduce energy use, though with varying degrees of rebound.

Our paper also adds to a well-established environmental literature that has developed models to study clean energy subsidies as a form of second-best climate policy (see Newell, Pizer and Raimi, 2019, for a review). This literature has been complemented more recently by several macro studies on subsidies for clean energy or clean innovation (e.g., Arkolakis and Walsh, 2023; Bistline, Mehrotra and Wolfram, 2023; Casey, Jeon and Traeger, 2023; Hassler, Krusell, Olovsson and Reiter, 2020; Hinkelmann, 2024). Unlike our work, which focuses explicitly on subsidies received by households, these earlier papers study the impacts of subsidies received by firms. Two papers that, like in our work, develop models to specifically study subsidies for household equipment are Colas and Saulnier (forthcoming), who study the optimal spatial distribution for subsidies to residential solar, and Kuhn and Schlattmann (2024) as mentioned above.

The paper proceeds as follows: Section 2 describes key facts from our survey and existing data sets on household energy use, clean equipment, and emissions. Section 3 develops our model of home production and energy use and Section 4 calibrates the model using data from our survey and from the CEX and RECS. Section 5 presents our quantitative results on household-focused climate policy and the emissions impacts of changes in public climate concern. Section 6 concludes.

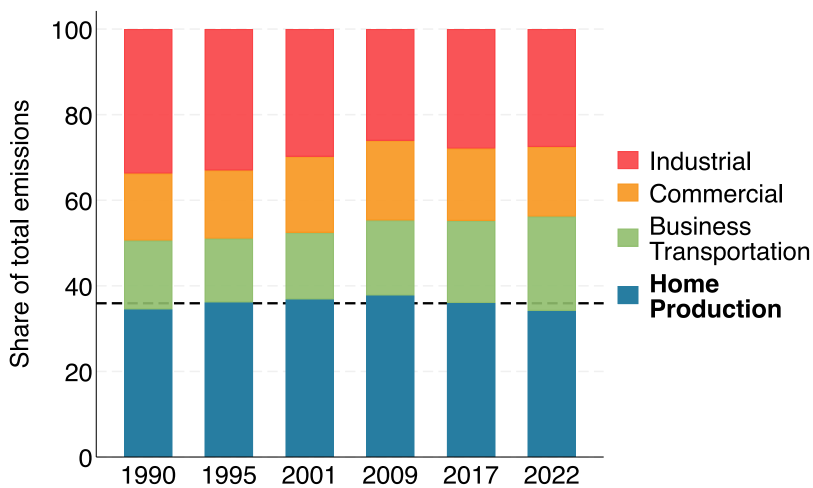
2. Household Emissions and Clean Equipment: Stylized Facts

We lay out the key stylized facts that motivate our model and quantitative analysis of household energy use. We begin by presenting two facts using existing data sets. We then document an additional set of facts from a new survey that we conducted on U.S. households.

2.1. Existing Data

Fact 1 *Household emissions account for approximately one third of aggregate emissions.*

Figure 1: U.S. Carbon Emissions by Sector



Note: The figure plots the share of emissions from each sector. The EIA divides emissions to four sectors: industrial, commercial, transportation, and residential. Emissions from home production equal residential emissions and a portion of transportation emissions. We separate transportation emissions into business and household transportation, as described in Appendix A.1. The dashed line represents the average home production share of emissions.

We define household emissions as emissions from households' direct use of energy for tasks such as heating, cooking, and driving. The Energy Information Administration (EIA) divides U.S. emissions into four sectors: commercial, industrial, transportation, and residential. Emissions from home production equal the emissions from the residential sector (from activities like heating and cooking) as well as a portion of the emissions from the transportation sector from household driving.[3] Figure 1 plots the share of U.S. emissions from home production (in blue) and the emissions from different aspects of firm production (in green, orange, and red). The key takeaway from Figure 1 is that emissions from home production are an important source of U.S. emissions, equal to approximately one third of total emissions. This fraction is remarkably stable over time.

[3] Appendix A.1 describes how we separate transportation emissions into emissions from household driving and emissions from business transportation.

Fact 2 *High-income households are more likely to use clean equipment and residential solar.*

It is widely known that high-income households are more likely to use solar panels and other types of clean equipment (see e.g., Dorsey and Wolfson, 2024; Borenstein and Davis, 2016). We present this result systematically for expositional purposes. We focus on the types of clean equipment included in the 2015 or 2020 RECS and/or the 2023 CEX: heat pumps, electric vehicles, energy-efficient appliances, and well-insulated housing.

To illustrate how the use of clean equipment and residential solar vary with household income, we estimate the following regression in each data set:

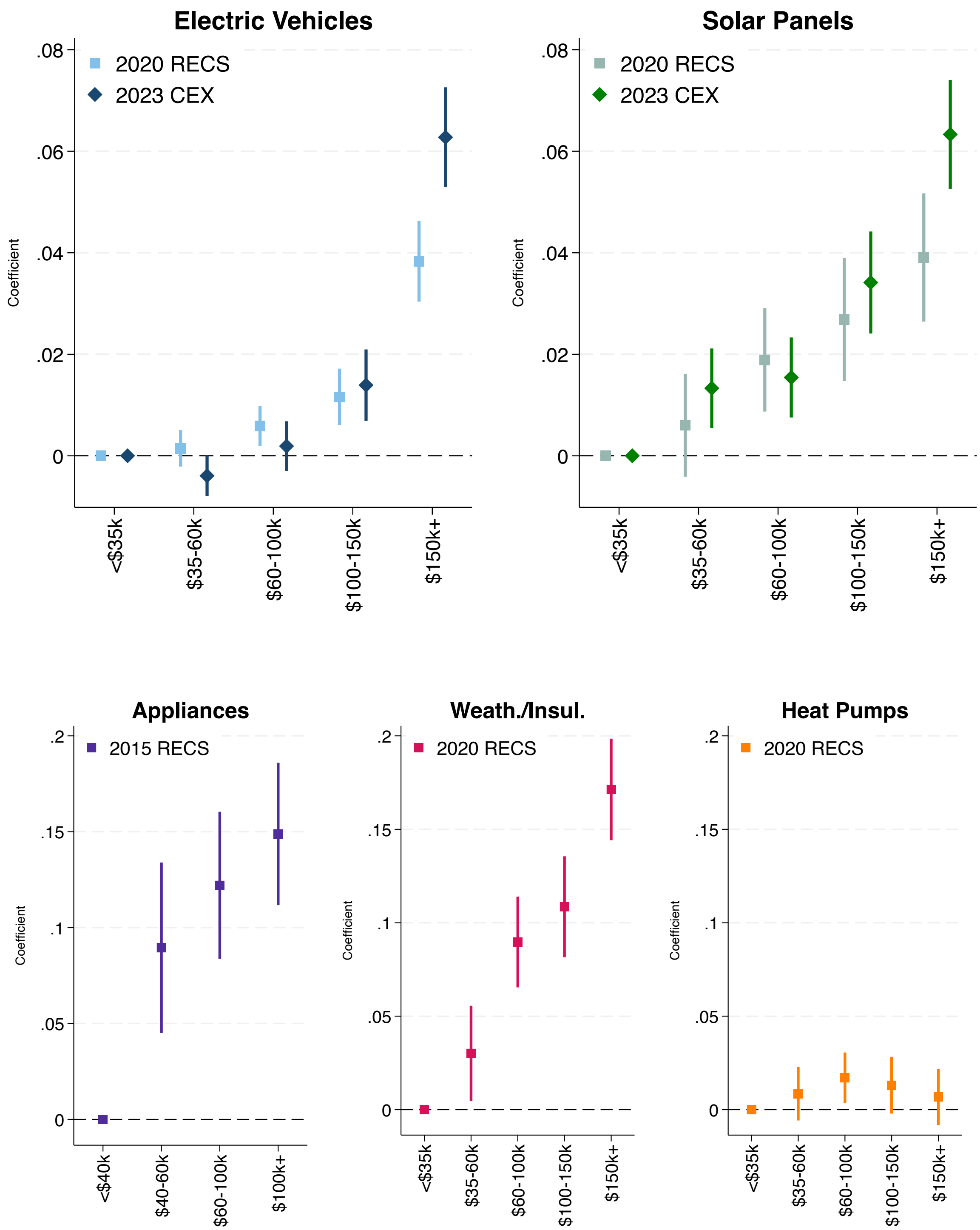
$$Y_{ik} = \alpha_k + \sum_j \beta_{jk}\text{Income}_{ij} + \gamma_{ik} + \eta_{ik} + \varepsilon_{ik}. \tag{1}$$

Variable Y_{ik} is an indicator that equals one if household i owns equipment type k and variable Income_{ij} is an indicator that equals one if the household is in income group j. Variables η_i and γ_i denote fixed effects for age and census region, respectively.

The top panels of Figure 2 report the estimated coefficients on income (the $\hat{\beta}'s$) in the RECS and the CEX for electric vehicles and solar panels. High-income households are more likely to have both items. For example, the fraction of households with an electric vehicle is four to six percentage points higher for households in the highest income group (those with income above \$150 thousand per year) relative to the lowest income group (those with income less than \$35 thousand per year, the omitted category).

The bottom panels of Figure 2 report the income coefficients for energy-efficient appliances, weatherization/insulation, and heat pumps, which are only included in the RECS. High-income households are also more likely to have relatively inexpensive clean equipment, such as energy-efficient appliances and weatherization/insulation. However, unlike the other types of clean equipment, high-income households are not more likely to have heat pumps. Consistent with this result, Davis (2024) finds that the adoption of heat pumps does not vary with household income and is instead strongly correlated with geography, climate, and electricity prices.

Figure 2: Variation in Clean Equipment with Household Income



Note: The figure plots the estimated coefficients on income from equation (1) in the RECS (squares) and CEX (diamonds) with 95 percent confidence intervals. Energy-efficient appliances are defined in the 2015 RECS as appliances that are Energy Star certified. This category is not available in the 2020 RECS. We define weatherization/insulation as having the highest insulation level, "well insulated".

2.2. New Survey Evidence

The existing data sets can help us understand which households use clean equipment and residential solar, but they do not contain information on why households make these choices. While standard economic reasoning predicts that households purchase clean equipment whenever it makes financial sense, households could also be motivated to use clean equipment by an environmental warm glow. We ran a new household survey to explore this possibility.

We ran the survey online through the Understanding America Study (UAS), a panel of 14,000 households managed by the University of Southern California. We conducted our survey on a nationally representative subset of 3,362 households from November 2023 to February 2024. We asked each household whether they owned/leased or had considered purchasing the following types of equipment: (i) all-electric or plug-in hybrid vehicle (electric vehicle), (ii) non-plug-in (NPI) hybrid vehicle, (iii) residential solar, (iv) heat pump heating and cooling, (v) energy-efficient appliances, and (vi) weatherization or insulation. We only asked homeowners about equipment that must be installed in the home. For solar panels and heat pumps, we asked homeowners to report if these items were present when they purchased their home.

We then asked a series of questions to understand *why* households had purchased or considered each piece of equipment. Respondents were given different factors and asked to rank them in order of importance. The factors included one environmental factor, "reducing carbon emissions," non-environmental factors such as "tax credits and rebates," "increasing the value of my home," and "reducing energy costs", as well as "other" with the option to specify a different reason.

Lastly, we asked households the Six Americas Short Survey (Chryst et al., 2018) to measure their levels of concern about climate change. The Six Americas classification was developed by Maibach et al. (2011) and has been used for over a decade to separate the population into six groups, the "Six Americas," that perceive and respond to climate change in distinct ways. The groups range from dismissive, those who think climate change is not happening, to alarmed, those who think climate change is an urgent threat. The Short Survey was developed to predict respondents' Six Americas type with only four questions (see Appendix A.3). We asked our survey respondents these questions and, based on their responses, assigned them to one of the six levels of climate change concern. We asked these questions at the end of our survey to ensure that they did not affect the responses to other questions.

The households in our sample are representative in that their geographic, demographic, and income characteristics broadly match those from the Current Population Survey (CPS) and the American Community Survey (ACS) (Appendix Figures A2-A4). We show in the Appendix that our results are robust to weights calibrated with iterative proportional fitting so that our sample precisely

Table 1: Percent of Households with Clean Equipment and Residential Solar

%	(1) Electric Veh.	(2) Hybrid (NPI)	(3) Solar Panels	(4) Heat Pumps	(5) Appl./Weath.
(a) Own/Lease					
All Households	4.9	16.4	*4.9*		
Homeowners	5.5	14.7	7.5	27.9	80.8
Renters	3.8	19.6	*0*		
(b) Considered					
All Households	33.5	32.7			
Homeowners	32.8	33.6	45.5	15.6	33
Renters	34.7	30.9			

Note: The table reports the fractions of households that own/lease each type of clean equipment (panel a) and the fraction of those who don't own/lease that have considered the clean equipment (panel b). Appendix Table A2 includes ownership rates for electric vehicles and hybrids which exclude those households who reported that they do not drive or do not need a car, ownership rates for solar panels among those in single-family homes, and the fraction of homeowners who *installed* solar panels or heat pumps themselves rather than buying a house which already had them.

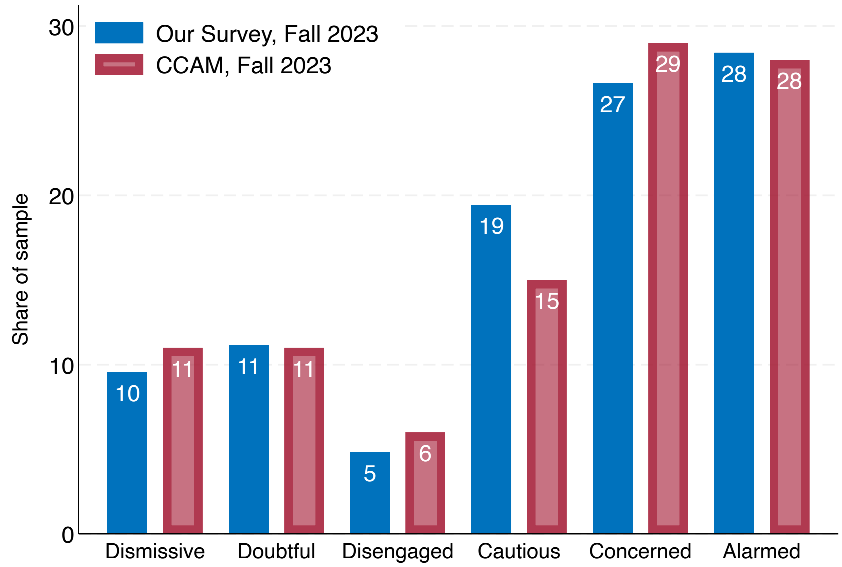
matches the CPS distributions of age, education, gender, income, race, and region.

Panel a of Table 1 reports the fraction of households in our sample that own (or lease) residential solar and each type of clean equipment. Electric vehicles are the least common, owned/leased by 5 percent of households, while energy-efficient appliances are the most common, owned/leased by 81 percent of homeowners. Panel b of Table 1 reports the share of households who do not own the clean equipment or residential solar but considered purchasing it. Almost half of homeowners who do not have solar panels have considered installing them, and one third of households without an electric vehicle have considered one.

Our survey matches the empirical patterns in the existing data sets quite well. Higher income households in our survey are substantially more likely to use residential solar and all types of clean equipment except heat pumps (see Appendix Figure A5), consistent with our findings in the RECS and the CEX in Fact 2.[4] We also compare the distribution of climate change concern in our survey to the distribution collected as part of the Climate Change and the American Mind (CCAM) project, a series of biannual surveys of public opinion on climate change run by Yale and George Mason universities. Figure 3 plots the fraction of households with each level of climate change concern in our survey (blue) and from the CCAM project over the same time period (red). The

[4]Note that clean equipment and residential solar ownership rates are slightly higher in our sample compared to the CEX and RECS (Appendix Table A1). This difference likely reflects the fact that use of clean equipment and residential solar has increased over time.

Figure 3: Distribution of Climate Change Concern



Note: The figure plots the percent of households with each level of climate change concern in our survey (blue filled) and from the CCAM project (red boxes).

distributions match quite closely.

2.3. Survey Facts

We discuss three new facts on household decisions to use clean equipment and residential solar from our survey data.

Fact 3 *Reducing emissions is important for some households' decisions to use clean equipment and residential solar.*

We focus on the portion of our survey in which we asked households to rank the factors that were most important in their decisions to purchase or to consider purchasing clean equipment and residential solar. Table 2 reports the share of households ranking each factor as either first or second most important. In line with standard economic reasoning, many households purchase clean equipment because it makes financial sense by reducing fuel or energy costs (row 2), or by allowing them to claim tax credits and rebates (row 3). However, a substantial portion of households also make these purchases because it reduces their carbon emissions (row 1), consistent with the notion that some households are motivated by an environmental warm glow.[5]

[5] Appendix Table A3a shows the same pattern with survey weights, and Appendix Table A3b shows the same pattern for households who have considered but not yet purchased clean equipment.

Table 2: Households Ranking Each Factor as First or Second Most Important

%	Electric Veh.	Hybrid (NPI)	Solar Panels	Heat Pumps	Appl./Weath.
(1) Reduce carbon emissions	44	35	27	17	23
(2) Reduce fuel costs	70	75			
energy costs			91	87	89
(3) Tax credits and rebates	33	27	44	22	25
(4) Performance, quiet, safety	39	47			
Raise home value			26	48	50
(5) Other	6	7	5	17	5
N	156	470	131	187	1718

Note: The table reports the fraction of households that ranked each factor (row) as either first or second most important for their decision to purchase a given type of equipment (column).

We use the term environmental preferences to refer the degree to which a household cares about their emissions. The results in Table 2 suggest considerable heterogeneity in environmental preferences across households. For example, among households who purchased an electric vehicle, 44 percent said that reducing carbon emissions was one of the two most important factors in their decision, suggesting strong environmental preferences, but 66 percent did not say that it was one of the two most important factors, suggesting weak environmental preferences.

Fact 4 *Environmental preferences are uncorrelated with income.*

We show that environmental preferences are uncorrelated with income. We measure environmental preferences in two ways: first, by whether the household ranked reducing carbon emissions as important for their decisions, as in Fact 3, and second, by the household's level of concern about climate change. We show in Appendix A.5 that these two measures are highly correlated.

Beginning with the first measure, we estimate the linear probability model:

$$Y_i = \alpha + \sum_{j=1} \beta_j \cdot (\text{Income})_{ij} + \eta_i + \gamma_i + \varepsilon_i \tag{2}$$

where Y_i is an indicator for whether household i ranked reducing carbon emissions as an important factor for their purchase of at least one type of clean equipment or residential solar. $(\text{Income})_{ij}$ is an indicator variable that equals one if household i is in income group j. Variables η_i and γ_i denote fixed effects for age and census region, respectively. Table 3 reports the results.

There are no statistically significant differences across income groups in the share of households who report that reducing carbon emissions is an important factor, with or without controls for age and region.[6,7] These results are perhaps surprising given the positive correlation between income and clean equipment ownership that we document in Fact 2. Income matters for what households actually purchase (Fact 2) but not for what they like (Fact 4).

Table 3: Percent Ranking Carbon Emissions as Important

	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
\$150k+	0.035	0.036	0.044	0.033
	(0.025)	(0.025)	(0.035)	(0.036)
\$100-150k	-0.012	-0.011	-0.023	-0.026
	(0.023)	(0.023)	(0.034)	(0.034)
\$60-100k	-0.031	-0.030	-0.048	-0.052
	(0.021)	(0.021)	(0.032)	(0.032)
\$35-60k	-0.023	-0.022	-0.035	-0.036
	(0.023)	(0.023)	(0.036)	(0.035)
Controls: Age, Region		✓		✓
Observations	2019	2019	2019	2019

Note: The table reports the results from equation (2) where the outcome is ranking reducing carbon emissions the most important (columns 1 and 2), or the first or second most important (columns 3 and 4) factor in their decision to purchase at least one type of clean equipment. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Similarly, we estimate equation (2) when the dependent variable is an indicator for whether the household ranked reducing carbon emissions as an important factor in their decision to *consider* solar or at least one type of clean equipment. Appendix Table A6 reports the analog of Table 3 for the considered regression. Again, we see no statically significant differences across income groups.

We repeat the analysis with our second measure of environmental preferences, the household's level of climate concern based on the Six Americas classification. This measure has the advantage that it is available for all households in our sample, not just those who already purchased or considered purchasing solar or clean equipment. Appendix Table A7 shows that the household's level of concern about climate change is also uncorrelated with income, consistent with the results in Table 3 and Appendix Table A6.

[6]These results are not specific to the linear probability model. Appendix Table A4 reports probit marginal effects for the same specification. The results are unchanged. Appendix Table A5 shows that the results are also unaffected by the use of survey weights.

[7]One possibility is that our income measure is too noisy to reveal any meaningful correlations. However, this is not likely because we closely match the correlations between income and clean equipment ownership in the RECS and CEX (see Appendix Figure A5).

Fact 5 *Households with stronger environmental preferences are more likely to use clean equipment and residential solar.*

We show that households with stronger environmental preferences are more likely to use clean equipment and residential solar, suggesting that environmental preferences are an important determinant of households' energy-related decisions. We estimate the following linear probability model:

$$Y_{ik} = \alpha_k + \beta_k \text{More Concerned}_i + \eta_{ik} + \nu_{ik} + \gamma_{ik} + \varepsilon_{ik} \tag{3}$$

where Y_{ik} is an indicator for whether household i had purchased equipment type k, More Concerned$_i$ is an indicator which equals one if household i is in either the Alarmed or the Concerned group. Approximately 55 percent of households fall into one of these two categories. Variables η_i, ν_i, and γ_i denote fixed effects for age, income, and census region, respectively. Table 4 reports the results.[8]

Overall, households with stronger environmental preferences are more likely to purchase clean equipment. For example, more-concerned households are five percentage points more likely to purchase an electric vehicle. Since only four percent of less-concerned households own electric vehicles (see Appendix Table A8), this result implies that more-concerned households are more than twice as likely to purchase an electric vehicle. Similarly, more-concerned households are 5 percentage points more likely to have solar panels.[9]

Panel b of Table 3 reports the analogous results when Y_{ik} is an indicator for whether the household considered purchasing equipment of type k.[10] We also see significant differences in the likelihood of *considering* the purchase of clean equipment by environmental preference. More-concerned households are 24 percentage points more likely to consider electric vehicles, 14 percentage points more likely to consider solar panels, and 16 percentage points more likely to consider energy-efficient appliances or weatherization/insulation.

We do not see a statistically significant difference in the likelihood of purchasing or considering heat pumps by environmental preference. Heat pumps have only recently been marketed as climate-friendly. It is possible that this messaging was not in place at the time many households replaced or considered replacing their heating and cooling systems. Moreover, Anderson and

[8]Appendix Table A9 reports the marginal effects from a probit regression, Appendix Table A10 reports a weighted version of the linear probability model. The results are largely unchanged. Appendix Tables A11 and A12 report separate results for each of the six levels of climate concern. Again, the overall patterns persist.

[9]Appendix Table A14 repeats in the analysis in Table 4 for heat pumps and solar panels among the subsample of households who choose to install these items. This exercise excludes households who purchased homes with heat pumps and solar panels already installed. The results are qualitatively similar.

[10]We drop all households who already purchased equipment of type k from the regression.

Table 4: Environmental Preferences and Clean-Equipment and Residential Solar Decisions

(a) Own/Lease

	(1) Electric Veh.	(2) Hybrid (NPI)	(3) Solar Panels	(4) Heat Pumps	(5) Appl./Weath.
More Concerned	0.047***	0.012	0.046*	-0.003	0.016
	(0.011)	(0.016)	(0.026)	(0.020)	(0.017)
FE: Age, Income, Region	✓	✓	✓	✓	✓
Observations	2154	2172	823	1980	2125
Adjusted R^2	0.073	0.023	0.100	0.053	0.042

(b) Considered

	(1) Electric Veh.	(2) Hybrid (NPI)	(3) Solar Panels	(4) Heat Pumps	(5) Appl./Weath.
More Concerned	0.244***	0.225***	0.136***	0.027	0.155***
	(0.020)	(0.022)	(0.037)	(0.019)	(0.055)
FE: Age. Income, Region	✓	✓	✓	✓	✓
Observations	1996	1683	672	1427	284
Adjusted R^2	0.126	0.088	0.034	0.019	0.061

Note: The table reports the results from equation (3) where the outcome is own/leasing (panel a) or considered (panel b) a given type of equipment. In columns (1) and (2), we drop households who reported that they do not drive or do not need a car. In column (3) the sample is restricted to households with single-family detached homes, excluding those who reported that solar panels are not feasible for their house/roof. Table A14 reports results for *installing* solar panels or heat pumps. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Kirkpatrick (forthcoming) find large variation in the private energy-cost savings from switching to heat pumps, from -$772 to $690 dollars per year, mainly driven by differences in climate, energy prices, and alternative fuel types. This substantial variation in pecuniary benefits could dominate any variation due to environmental preferences in the data.

3. Model

Household emissions depend on two key margins. The first is the total amount of home production the household undertakes. For example, how much do they drive, cook, or use the washing machine? How big of a space do they heat and how warm do they make it? The second is the equipment the household uses for their home production. For example, do they drive an electric vehicle or a gasoline car? Do they have a heat pump or a natural gas furnace? Do they use energy-efficient appliances? These two simple margins form the basis for our model of home production and household energy use.

Our model augments the standard home production framework (Becker, 1965; Benhabib et al., 1991) to include a continuum of tasks (as in Acemoglu and Restrepo, 2019) with clean and dirty production technologies for each task (as in Aghion et al., 2024). Home production tasks include heating, transport, laundry and so on. Households in the model can also use residential solar to produce clean (carbon-free) energy. Drawing from our survey evidence, households have heterogeneous distaste over their own carbon emissions.

3.1. Households Preferences and Endowments

The economy is populated by a continuum of measure one of households. Preferences are:

$$u(c_i, h_i, v_i) = \chi \ln(c_i) + (1-\chi)\ln(h_i) - \theta_i v_i, \tag{4}$$

where c_i is consumption of market goods, h_i is home production, and v_i is the household's own carbon emissions. Home production depends on a CES aggregate of home production tasks,

$$h_i = \left[\int_0^1 q_i(j)^{\frac{\varepsilon-1}{\varepsilon}} dj\right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where $q_i(j), j \in [0,1]$ denotes household i's production of task j and parameter ε is the elasticity of substitution across tasks. To produce each task, the household can use a dirty technology that requires energy or a clean technology that does not. The production functions for task j using the dirty and clean technology are:

$$q_i(j) = \begin{cases} \min[x_i^d(j), \frac{1}{\mu} e_i(j)] & : \text{dirty technology} \\ x_i^c(j)\Phi(j) & : \text{clean technology} \end{cases} \tag{5}$$

If the household uses the dirty technology to produce task j, then they must combine dirty equipment, $x^d(j)$, with energy, $e(j)$, in fixed proportions. If instead they use the clean technology, then they can produce task j directly from clean equipment, $x^c(j)$, without any energy.

Function $\Phi(j)$ is the relative productivity of producing with the clean technology. We arrange the tasks on the unit interval so that tasks with a higher index have higher clean productivity, implying that $\Phi(j)$ is strictly increasing in j. We assume the simple functional form:

$$\Phi(j) = \phi j.$$

For example, compare the tasks of lighting and heating. The household can produce lighting using dirty equipment (e.g., an incandescent bulb) and energy or clean equipment, (e.g., an LED bulb) and very little energy. It is cheaper to produce lighting with clean equipment than with dirty equipment (including both the energy and the light-bulb costs). In contrast, depending on the electricity price and the climate, it can be more expensive to produce heating with clean equipment (e.g., a heat pump) than with dirty equipment (e.g., a natural gas furnace) (Anderson and Kirkpatrick, forthcoming). Thus, we interpret $\Phi(\text{lighting}) > \Phi(\text{heating})$ and we view lighting as being ordered higher than heating along the continuum.

We model environmental preferences as household distaste for their own carbon emissions, v_i, that they generate through home production. The strength of this distaste, captured by $\theta_i \in [0, \infty)$ varies across households. Some households have strong distaste ($\theta >> 0$), implying that they care a lot about reducing their own emissions, while other households have no distaste ($\theta = 0$), implying that they do not care about reducing their emissions.

Each household i is endowed with one unit of time with productivity, ζ_i. The household supplies their effective labor, ζ_i, to firms and earns labor income, $w\zeta_i$, where w is the market wage per efficiency unit of labor. This exogenous model of labor supply abstracts from the household's allocation of time between home work, market work, and leisure. While this channel is important for earlier work on home production, it is not a key determinant of household emissions, the focus of the present paper. For example, the emissions from heating depend on amount of heating produced and the type of heating equipment, not on the amount of time the household spends setting the temperature. As such, we build the model to focus explicitly on the equipment and energy that households use to produce home production tasks.

3.2. Residential Solar

Households can purchase residential solar to generate clean (carbon-free) energy. Residential solar differs from the equipment discussed in Section 3.1 in that it does not directly produce home-services tasks. Instead, households substitute the solar energy they produce for the energy that they would otherwise purchase to decrease their energy expenses and carbon emissions.

If the household purchases solar, the number of panels they purchase, $S(\zeta_i)$, is exogenous and varies with the household's (fixed) labor productivity, ζ_i. The intuition is that the amount of solar a household can install is limited by the size of their roof. Higher income households tend to have larger houses with bigger roofs, and thus can install more solar panels. The household's production of solar energy, e^s, is directly proportional to the number of panels: $e^s_i = \alpha s_i$, where $s_i \in \{0, S(\zeta_i)\}$.

In practice, a household's decision to install solar depends on many factors. Some of these factors we directly model, such as income and environmental preferences, but other factors are outside of our model, such as the tilt, orientation, and shadiness of the roof, the sunniness of the location, and the roof quality and material. To account for the factors outside of our model, we assume that households draw idiosyncratic solar taste shocks. Households draw a separate taste shock for each solar installation option: install, do not install. The taste shocks are independently and identically distributed across households and installation options. At the start of the period, the household draws the values of the taste shocks from a Gumbel distribution with scale parameter γ.

3.3. Household Emissions

The carbon emissions for household i, v_i, depend on their energy use and on their solar energy production,

$$v_i = \eta \left(\int_0^1 e_i(j)dj - e_i^s \right).$$

The integral $\int_0^1 e_i(j)dj$ is the household's total energy demand and e_i^s is the amount of this demand that is met by the household's production of solar energy. The difference, $\int_0^1 e_i(j)dj - e_i^s$ equals the household's use of carbon energy. Parameter η denotes the carbon intensity of carbon energy.

3.4. Analysis of the Household Problem

Households maximize utility plus the solar taste shock. They choose consumption, whether to install solar, and, for each task, clean and dirty equipment and energy. Let $\Omega_i \equiv \{c_i, \{x_i^c(j), x_i^d(j), e_i(j)\}\forall j\}$ denote the set of choice variables exclusive of the solar installation decision. The household's objective function equals:

$$\max_{s_i \in \{0, S(\zeta_i)\}} \left\{ \max_{\Omega_i} u(c_i, h_i, v_i) + \Upsilon_i^s,\ \max_{\Omega_i} u(c_i, h_i, v_i) + \Upsilon_i^{ns} \right\},$$

where Υ_i^s and Υ_i^{ns} denote the realizations of the solar taste shock if the household does and does not install solar, respectively.

The household preforms this optimization subject to the budget constraint,

$$w\zeta_i = c_i + p^c \int_0^1 x_i^c(j)dj + p^d \int_0^1 x_i^d(j)dj + p^e \left(\int_0^1 e_i(j)dj - e_i^s \right) + p^s s_i, \tag{6}$$

and the non-negativity constraints,

$$c_i \geq 0,\ \{x_i^c(j) \geq 0,\ x_i^d(j) \geq 0,\ e_i(j) \geq 0\}\forall j.$$

Variables p^c, p^d, p^e, and p^s denote the relative prices of clean equipment, dirty equipment, energy, and solar panels, respectively. In the analysis that follows, let λ_i denote the multiplier on the budget constraint for household i.

We study the factors that affect the household's clean equipment and solar decisions. Beginning with clean equipment, we have the following proposition.

Proposition 1 *For each household i, there exists a cutoff*

$$J_i^\star \equiv \frac{p^c}{\phi(p^d + \mu p^e + \frac{\mu\theta_i}{\lambda_i})}, \tag{7}$$

such that the household will use the clean technology for all tasks with $j \geq J_i^\star$ *and will use the dirty technology for all tasks with* $j < J_i^\star$.

Proof The first order condition for household i for task j equals:

$$\left(\frac{1-\chi}{h_i}\right)\left(\frac{h_i}{q_i(j)}\right)^{\frac{1}{\varepsilon}} = \begin{cases} \lambda_i \frac{p^c}{\phi j} & : \text{if clean} \\ \lambda_i(p^d + \mu p^e) + \mu\theta_i & : \text{if dirty.} \end{cases}$$

The household will produce with the clean technology if the marginal utility cost of producing with the clean technology is less than the marginal utility cost of producing with the dirty technology:

$$\lambda_i \frac{p^c}{\phi j} \leq \lambda_i(p^d + \mu p^e) + \mu\theta_i. \tag{8}$$

$J_i^\star$ is the index that equates the marginal costs. Since the marginal utility cost of producing with the clean technology (left-hand-side of (8)) is strictly decreasing in j, the household will use the clean technology for all tasks with $j \geq J_i^\star$. Q.E.D.

We exploit the properties of $J^\star$ to show that our model matches the empirical relationships between income, environmental preferences, and clean equipment from Section 2.

Corollary 1 *Use of clean equipment is positively correlated with income.*

The cutoff, $J^\star$ is increasing in λ_i, the shadow-value of income. Thus, all else constant, higher income households choose a lower cutoff, implying that they use clean equipment for more tasks, consistent with Fact 2.

The intuition for this result stems from the non-homothetic specification of preferences (equation (4)). The marginal utility of consumption and home production falls as both quantities rise, but the marginal disutility of emissions does not depend on the level of emissions. As a result, reducing emissions is a normal good for all households with $\theta > 0$. Higher income households purchase more emissions reduction by using clean equipment for more tasks. As in our survey, the positive correlation between clean equipment and income does not require a positive correlation between environmental preferences and income. Environmental preferences matter for what households want, but income matters for what they actually purchase.

Corollary 2 *Use of clean equipment is positively correlated with environmental preferences.*

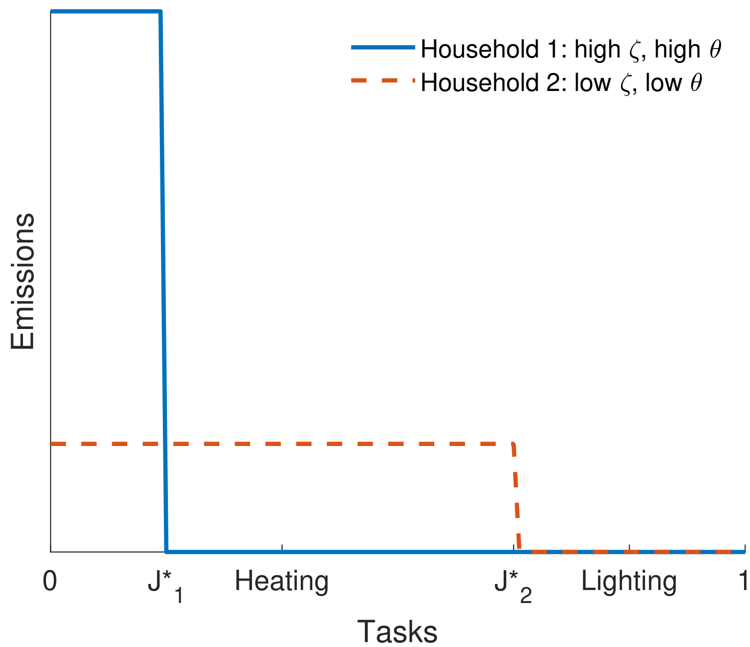
The cutoff $J^\star$ decreases with θ, implying that households with stronger environmental preferences use clean equipment for more tasks, consistent with Fact 5.

To demonstrate the implications of corollaries one and two, Figure 4 plots household emissions from each task for two different households. The households differ in their income and environmental preferences, but have the same total emissions, equal to the area under each curve in Figure 4. Household one has high income and strong environmental preferences. Corollaries one and two imply that this household will use clean equipment for many tasks (cutoff $J_1^\star$ is relatively low), reducing their emissions. However, since they have high income, the household produces more home production, increasing their emissions from the tasks for which they use dirty equipment.[11] In contrast, household two has low income and weak environmental preferences. Corollaries one and two imply that this household will use clean equipment for few tasks (cutoff $J_2^\star$ is relatively high), increasing their emissions. However, since they have low income, the household produces less home production, reducing their emissions from the tasks for which they use dirty equipment. In principle, either household could have larger total emissions; we have drawn the case for which they are equal.

We can place specific tasks at different points on the x-axis, based on the relative productivity of the clean equipment for that task. For example, as discussed above, we interpret clean equipment for lighting (LED bulbs) as has having relatively high productivity and clean equipment for heating (heat pump) as having relatively low productivity. We place lighting and heating along the x-axis in Figure 4 so that lighting is to the right of heating. As drawn, household one uses clean equipment for both lighting and heating, but household two only uses clean equipment for lighting.

[11] We focus on the empirically relevant region of the parameter space in which the income-elasticity of demand for each task is positive for both households.

Figure 4: Emissions From Home Production Tasks For Two Households



Note: The figure plots emissions from each task for two hypothetical households, one with high income and strong environmental preferences (solid blue line) and a second with low income and weak environmental preferences (dashed orange line). The tasks are aranged along the x-axis in order of increasing productivity of the clean equipment.

The variation in the cutoff $J^\star$ across households results from the inclusion of environmental preferences in the model. If we abstract from environmental preferences ($\theta_i = 0$, $\forall i$), then all households choose the same cutoff, $J^\star = p^c/(\phi(p^d + \mu p^e))$, implying that they all use clean equipment for the exact same set of tasks. This prediction is not consistent with our survey data or with RECS. For example, in our survey data, we document considerable heterogeneity in the fraction of households that use each type of clean equipment and in the fraction of households that consider adopting each type of clean equipment (see Table 1).[12] Such variation suggests that clean equipment adoption decisions are heterogeneous across households, a feature our model without out environmental preferences cannot capture.

We turn to the household's decision to install solar.

[12]While some of this heterogeneity in the data could result from the slow adoption of relatively new clean technologies, our survey data suggest that slow adoption is not the dominant factor. For example, only 35 percent of households without an electric vehicle cite not needing a new car as their reason for not buying an electric vehicle.

Proposition 2 *The probability a household with productivity ζ_i and environmental preferences θ_i installs solar equals*

$$Prob^s(\zeta_i,\theta_i) = \frac{\exp(\gamma^{-1}\hat{u}^s(\zeta_i,\theta_i))}{\exp(\gamma^{-1}\hat{u}^s(\zeta_i,\theta_i)) + \exp(\gamma^{-1}\hat{u}^{ns}(\zeta_i,\theta_i)},$$

where $\hat{u}^s$ and $\hat{u}^{ns}$ denote the household's optimized utility with and without solar, respectively.

The scale parameter, γ, controls the strength of the correlations between the probability a household has solar and their income and environmental preferences. As γ approaches infinity, the taste shocks become the only factor that affects the household's solar decision and these correlations approach zero.

3.5. Firms

A unit mass of perfectly competitive firms produce the final consumption good from labor, and produce clean and dirty equipment, carbon energy, and solar panels from units of final good. The production functions are:

$$Y = AN, \quad X^c = A^cY^c, \quad X^d = A^dY^d, \quad E = A^eY^e, \quad S = A^sY^s$$

where N denotes total effective labor used to produce the final good and Y^c, Y^d, Y^e, Y^s denote units of final good used to produce clean equipment, dirty equipment, energy, and solar panels respectively. The final good is the numeraire.

3.6. Competitive Equilibrium

We define a *competitive equilibrium* as a set of prices: $\{w, p^c, p^d, p^e, p^s\}$, allocations for each household i, $\{c_i, s_i, \{x_i^c(j), x_i^d(j), e_i(j)\}\forall j\}$, production plans for firms $\{N, Y^c, Y^d, Y^e, Y^s\}$ such that:

1. Given prices, household allocations solve the household's optimization problem.

2. Given prices, firm allocations maximize profits.

3. The labor market clears

$$N = \int_0^1 \zeta_i di.$$

4. The energy, equipment, and solar markets clear:

$$E=\int_0^1\left(\int_0^1 e_i(j)dj-e_i^s\right)di \quad X^c=\int_0^1\int_0^1 x_i^c(j)djdi \quad X^d=\int_0^1\int_0^1 x_i^d(j)djdi, \quad S=\int_0^1 s_i di.$$

5. The resource constraint holds:

$$Y+\int_0^1 e_i^s di=\int_0^1 c_i di+Y^c+Y^d+Y^e+Y^s.$$

Firm profit maximization and market clearing yield the equilibrium expressions for the wage and the relative prices of clean equipment, dirty equipment, energy, and solar panels:

$$w=A \quad p^c=\frac{1}{A^c} \quad p^d=\frac{1}{A^d} \quad p^e=\frac{1}{A^e} \quad p^s=\frac{1}{A^s}.$$

4. Model Calibration and Validation

To simulate the effects of household-focused climate policy and changes in public attitudes towards climate change, we need to parameterize the model to match key features of the U.S. data. We use three data sets: (1) our survey data, (2) the 2020 RECS, and (3) the 2022 CEX. We take some parameters directly from the data. Given these parameters, we jointly calibrate the remaining parameters so that a set of moments in the model match their corresponding empirical targets.

4.1. External Calibration

We determine the distribution of environmental preferences directly from our survey data. We assign households to one of the six categories of climate concern from Figure 3. We assume that each level of concern maps to a unique value of $\theta\in[0,\bar{\theta}]$. Dismissive households have $\theta=0$, alarmed households have $\theta=\bar{\theta}$, households in category $i\in[2,5]$ have value $\theta_i=(i-1)\bar{\theta}/5$. We take the fraction of households in each category directly from our survey.

Relative productivities A^e, A^d, A^c, and A^s pin down the units of energy, dirty equipment, clean equipment, and solar panels. Parameter η pins down the units of carbon emissions. None of these units are relevant for our model. We normalize these parameters to unity. We set the value of the cross-task elasticity of substitution, ε equal to 0.5, in line with the values commonly used in the task literature (see e.g., Humlum, 2021; Acemoglu and Restrepo, 2019).

4.2. Internal Calibration

We jointly choose the remaining parameters to match a set of empirical targets. While all targets are jointly determined, some targets are more important for some parameters than others. We discuss each parameter and its primary target in turn.

Parameter χ determines the relative utility benefits from home production tasks. We choose χ to match the average ratio from the CEX of non-energy expenditures on home production (i.e., expenditures on housing and equipment) relative to total consumption expenditures, equal to 0.30.

Parameter ϕ is primarily pinned down by the average energy expenditure share. All else constant, higher levels of ϕ imply a lower cutoff $J^\star$ (see equation (7)), which, in turn, implies that the household uses clean equipment for more tasks, reducing their energy expenditure share. We choose ϕ to match average energy expenditure share in the CEX, equal to 0.098. Parameter $\bar{\theta}$ controls how energy expenditure share changes with income. If $\bar{\theta} = 0$, then $\theta = 0$ for all households and energy expenditure share is constant across income groups. Positive values of $\bar{\theta}$ imply that reducing emissions is a normal good for some households (those with $\theta > 0$), causing energy budget share to fall more steeply with income. We choose $\bar{\theta}$ to match the ratio of the average energy expenditure share among the top half of the income distribution relative to the bottom half of the distribution.

Leontief parameter μ is disciplined by the price elasticity of household demand for energy. μ determines the relative importance of energy costs as a component of total cost for the tasks the household produces with the dirty technology. Higher values of μ increase the relative importance of energy costs, which, in turn, increase the magnitude of the price elasticity of energy demand. In a meta-analysis of price elasticities of energy demand, Labandeira, Labeagac and Lopez-Otero (2017), find estimated long-run elasticities ranging from -0.77 to -0.19 depending on the energy product in question. We target a value of -0.62, which is their mean long-run estimate for the residential sector, and not too far from their mean overall estimate of -0.52.

We choose the productivity of solar, α, to match the fraction of households with residential solar in our survey, equal to 4.9 percent.[13] The Gumbel scale parameter controls the relative importance of the taste shocks compared to income and environmental preferences in the household's decision to install solar. We choose the scale parameter to match the portion of households with solar who are more-concerned, as defined in Fact 5, equal to 0.61.

It remains to choose the amount of solar a household installs, conditional on their labor productivity, $S(\zeta_i)$. Many utility companies use net-metering which implies that households are only compensated for solar energy they produce up to the amount of electricity they consume. As a

[13]Following the CEX, we only ask homeowners about residential solar, implicitly assuming that solar is zero for renters. Consistent with this assumption, only one percent of renters have solar panels in the 2020 RECS.

result, households are typically advised to install the amount of solar panels necessary to meet their electricity needs. Based on these incentives, we choose $S(\zeta_i)$ for each value of ζ so that, on average, the household's solar output equals the empirical fraction of household energy use from electricity, 0.17.[14]

Table 5: Model Fit

Target	Model	Data
Equipment expenditure share	0.30	0.30
Price elasticity of energy demand	-0.62	-0.62
Energy expenditure share	0.10	0.10
Energy expenditure share ratio: top half to bottom half	0.72	0.72
Variance of log expenditures	0.66	0.66
Fraction of solar HHs who are more concerned	0.61	0.61

Note: The table reports the values of the targeted moments in the model (column 1) and in the data (column 2).

Finally, we divide households into ten equally sized income groups. We assume labor productivity is log-normally distributed with mean μ_ζ and variance σ_ζ^2. We normalize the mean to unity and we choose the variance to match the variance of log expenditures from the CEX, equal to 0.66.

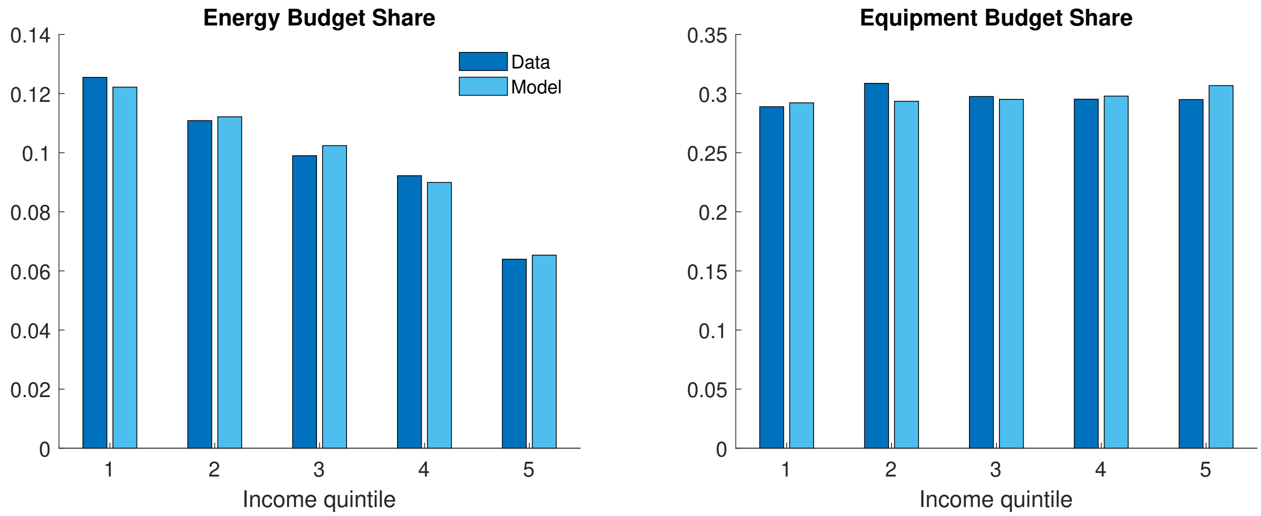
Table 5 reports the values of the moments in the model and in the data. The model fits the data quite closely. Table 6 summarizes the values of the calibrated parameters.

Table 6: Main Parameter Values

Parameter	Value
Consumption exponent: χ	0.57
Cross-task elasticity of substitution: ε	0.50
Maximum value of θ: $\bar{\theta}$	0.96
Leontief parameter: μ	0.68
Clean-equipment productivity scaler: ϕ	0.77
Gumbel scale parameter: γ	0.06
Solar productivity: α	0.08
Variance of labor productivity: σ_ζ^2	0.96

Note: The table reports the values of the calibrated parameters. The calibrated values of $S(\zeta)$ and ζ are in Appendix B.

Figure 5: External Validation: Energy and Equipment Budget Shares



Note: The left and right panels plot energy budget share and equipment budget share respectively by income quintile in the model (dark blue) and data (light blue). Quintile one corresponds to the lowest income group.

4.3. External Validation

Utility in our model is atypical in that it depends on tasks and carbon emissions in addition to consumption. As such, it is important to ensure that our model can replicate the patterns of household behavior that we see in the data. Specifically, we compare the correlations between income and expenditures on energy, equipment, and solar in the model and the data.

The left panel of Figure 5 plots energy budget share across income groups in the model (light blue) and the CEX (dark blue). In the calibration, we target the difference in energy expenditure share between the top and bottom halves of the income distribution. Figure 5 demonstrates that the model also does well matching the more micro variation between income and energy budget share.

The right panel of Figure 5 plots equipment budget share across income groups in the model and the CEX. In the calibration, we target average equipment budget share, but we do not target the variation across income groups. Equipment budget share in the CEX is relatively constant across income groups. The model matches this pattern quite closely.

Appendix Figure B1 plots energy and equipment expenditures in levels instead of as shares in both the model and the data. Both energy and equipment expenditures increase with income, and, as one would expect from Figure 5, the magnitudes are similar between the model and the data.

We also analyze how income affects the likelihood that a household uses residential solar in the model compared to our survey data. High-income households in the model are 3 percentage points

[14] Data on household electricity use are from EIA Table 2.2. Appendix A.1 explains how we calculate household energy consumption.

more likely to use solar than low-income households. To determine the corresponding empirical relationship, we run the following regression in our survey data:

$$\text{solar}_i = \beta_0 + \beta_1(\text{high income})_i + \gamma_i + \varepsilon_i.$$

The variables solar_i and $(\text{high income})_i$ are indicator variables which equal 1 if the household has solar or is high (above median) income, respectively. Variable γ_i denotes state fixed effects. The estimated value of $\beta_1 = 0.04$, implying that high-income households are 4 percentage points more likely to have solar than low-income households, similar to the model value.

Overall, the calibrated model matches the empirical patterns quite well. The decline in energy budget share with income is similar between the model and the data, and equipment budget share is relatively constant across income groups. High-income households are approximately three or four percentage points more likely to use solar.

5. Quantitative Results

We first quantify the key determinants of household emissions and how they vary across households. We next analyze the impacts of household-focused climate policies and solve for the climate policy that minimizes the cost of reaching an emissions target. Finally, we study the potential for changes in public attitudes towards climate change to impact aggregate household emissions.

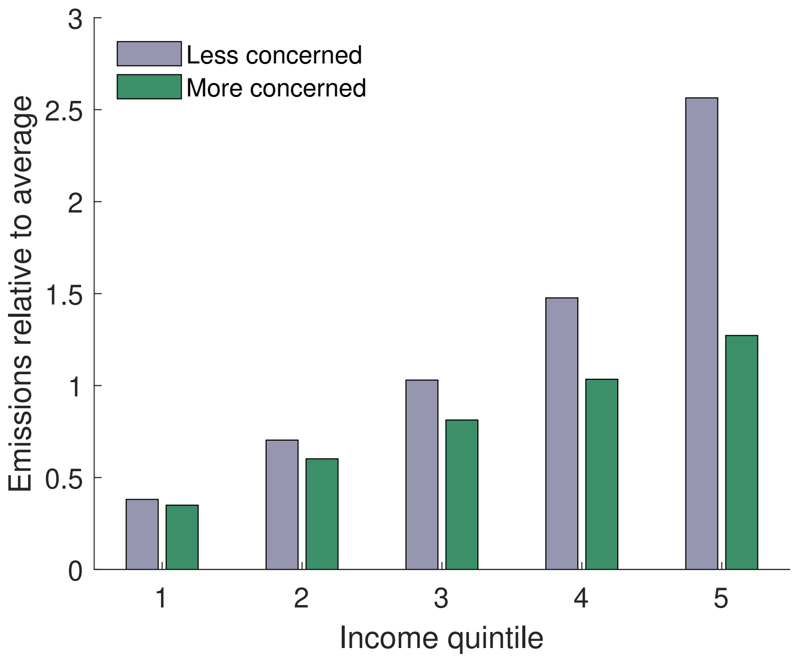
5.1. Household Emissions: Determinants and Distribution

Figure 6 plots average emissions by income quintile and environmental preference group. As in Fact 5, we collapse households into two environmental preference groups, more concerned, those that are either concerned or alarmed, and less concerned, those that are either dismissive, doubtful, disengaged or cautious. 55 percent of households are in the more-concerned group. The units of the y-axis are emissions relative to the emissions of the average household. For example, a value of 2 means that the household emits twice as much as the average household.

Figure 6 reveals two important patterns. First, emissions increase substantially with income. At the extreme, emissions for the average household in the fifth income quintile are over five times higher than emissions for the average household in the first income quintile. This result is perhaps expected given that household energy use increases substantially with income in both the model and the data (see Appendix Figure B1) and emissions are closely linked to energy use.

To understand why energy use and emissions increase with income, Figure 7 plots two key determinants of household emissions; the level of home production, h_i, and the energy efficiency of

Figure 6: Distribution of Household Emissions



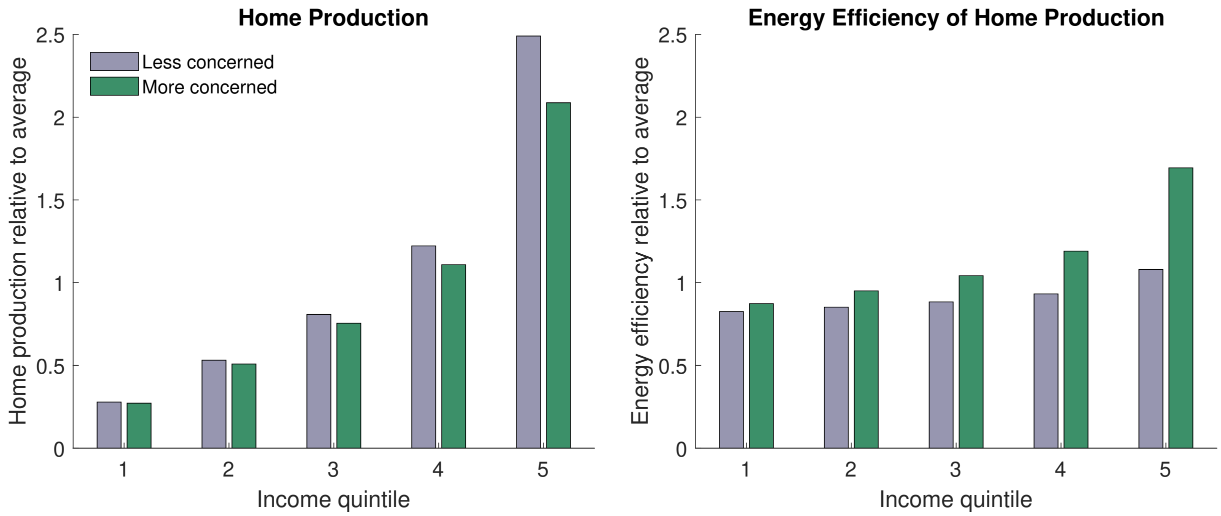
Note: The figure plots household emissions, by income quintile and environmental preference group. The units of the y-axis equal emissions relative to the emissions of the average household.

home production, h_i/e_i where $e_i \equiv \int_0^1 e_i(j)dj$. Household emissions also depend on residential solar, but so few households use solar in the baseline (less than five percent) that it is not an important driver of the aggregate patterns.

Home production increases with income (left panel of Figure 7), pushing up household energy use and emissions. For example, high-income households tend to have larger houses and thus use more energy for heating and cooling. Energy efficiency also increases with income (right panel of Figure 7), somewhat muting the increase in energy use from more home production. The intuition follows directly from Corollary 1. High-income households use clean equipment for more tasks, increasing their energy efficiency. Household emissions rise with income in Figure 6 because the increase in home production dominates the increase in efficiency.

The second key pattern from Figure 6 is that environmental preferences have a large effect on emissions for high-income households and almost no effect for low-income households. Among households in the fifth income quintile, average emissions among less-concerned households are more than double average emissions among more-concerned households. In contrast, among households in the first income quintile, average emissions among less-concerned households are only 9 percent higher than average emissions among more-concerned households. The intuition stems from the result that reducing emissions is a normal good. High-income households with strong environmental preferences purchase more emissions reduction than low-income households with strong environmental preferences. Consequently, the impact of environmental preferences on emissions increases with income.

Figure 7: Determinants of Household Emissions



Note: The left and right panels plot household home production, h_i and energy efficiency of home production, h_i/e_i where $e_i \equiv \int_0^1 e_i(j)dj$, respectively, by income quintile and environmental preference group. The units on the y-axis equal the value of the plotted variable relative to its value for the average household in the economy.

5.2. Household-Focused Climate Policy

We consider the impact of different policies designed to reduce household emissions. Policymakers face two primary considerations in their design of household climate policy: (1) determining which equipment to subsidize, and (2) identifying which households should be eligible to receive the subsidy. For example, the IRA includes subsidies for solar panels and particular types of clean equipment, such as electric vehicles and heat pumps. Some of the subsidies have income caps, implying that only households with income below the threshold are eligible to receive the subsidy.

To start, we examine the effect of two simple policies for which all households are eligible; a subsidy for all clean equipment and a subsidy for solar. We then solve for the subsidy policy that minimizes the cost of emissions reduction when the policymaker can choose the subsidized equipment and the eligible income groups. We choose the size of the subsidy in each experiment so that it reduces household emissions by 10 percent, loosely in line with the IRA projections.[15] We finance the subsidies with a flat tax on labor income.

Clean-Equipment Subsidy. A clean-equipment subsidy, $s^c > 0$, reduces the price of all clean

[15] Bistline et al. (2023) project that the IRA will reduce economy-wide emissions by approximately 15 percent relative to a scenario without the IRA. However, much of this reduction is through improvements in the electricity sector, suggesting that the decrease in household emissions without changes to the electricity sector, the analog to our model, will be smaller.

equipment from p^c to $(1-s^c)p^c$. All households are eligible to receive the subsidy. We find that the subsidy required to attain the emissions target equals 10 percent and the associated labor income tax equals 2.3 percent.

Table 7: Aggregate Effects of Household Climate Policies

	Subsidy Policy		
	Clean-equipment	Solar	Cost-minimizing
%Δ Emissions	-10.0	-10.0	-10.0
%Δ Clean equipment	20.7	-6.9	15.1
%Δ Dirty equipment	-10.0	-3.9	-9.9
%Δ Solar energy	-6.5	438.1	-2.6
%Δ Home production	2.1	-5.0	-0.0
%Δ Consumption	-2.8	-5.6	-1.2
Policy cost (% of GDP)	2.3	5.4	0.8

Note: The table reports the aggregate effects of a clean-equipment subsidy (column 1) a solar subsidy (column 2) and the cost-minimizing subsidy (column 3).

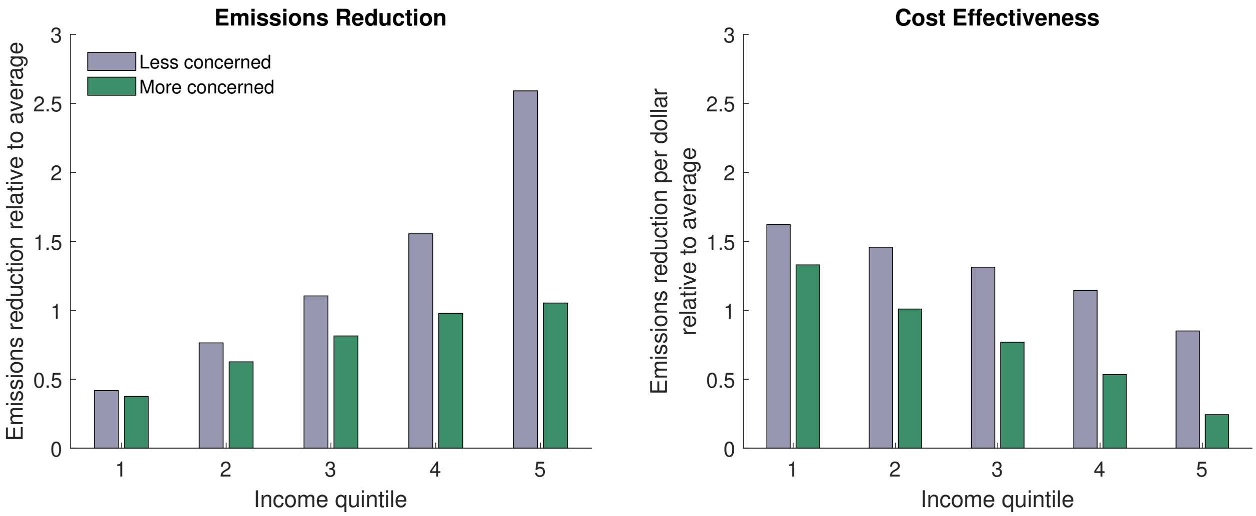
The first column of Table 7 reports the aggregate effects of the clean-equipment subsidy. The policy leads to a 21 percent increase in clean equipment and a 10 percent decrease in dirty equipment. The signs of these effects are evident from the expression for the cutoff, $J^{\star}$, in equation (7). The subsidy reduces the relative price of clean equipment, which, in turn, reduces the cutoff, implying that households use clean equipment for more tasks.

By making clean equipment cheaper, the subsidy reduces the relative price of home production. Households increase home production by 2 percent in response. Similarly, the subsidy decreases the relative cost of reducing emissions though clean equipment compared to solar, leading to a small decline in solar energy production. Finally, the cost of attaining the emissions target using a subsidy to all clean equipment equals 2.3 percent of GDP.

A key element of household-focused climate policy is which households are eligible for the policy. Of particular interest is how income affects eligibility; should the subsidy apply to all households, as in the case of the clean-equipment subsidy, or should the subsidy phase out with income in the sense that only lower income households are eligible? To provide insights on the tradeoffs associated with an income phase out, Figure 8 plots the distribution of emissions reduction in response to the subsidy (left panel) and of the cost effectiveness of the emissions reduction (right panel). We measure cost effectiveness as the household's emissions reduction divided by their implicit subsidy receipts, where implicit subsidy receipts for household i equal $s^c p^c \int_{J_i^{\star}}^{1} x_i^c(j)dj$.

The two panels of Figure 8 present a potential tension when considering an income phase out. High-income households, especially those with weak environmental preferences, reduce emis-

Figure 8: Distribution of Emissions Reduction and Cost Effectiveness: Clean-Equipment Subsidy



Note: The left and right panels plot emissions reduction, emissions reduction per dollar of implicit subsidy payments by income quintile and environmental preference group. The units on the y-axis show the value of the plotted variable relative to its value for the average household in the economy.

sions the most in response to the subsidy (left panel), because they emit the most without the subsidy. Using an income phase out to exclude these households from the policy would require policymakers to use a larger subsidy to reach the emissions target, potentially raising the policy cost.

On the other hand, high-income households, especially those with strong environmental preferences, are the least cost-effective (right panel). These households are largely inframarginal because, in the absence of the subsidy, they use clean equipment for more tasks. Thus, the subsidy subsidizes more equipment that they would have bought anyway, reducing its cost effectiveness. Using an income phase to exclude these households would focus the policy on most cost-effective segment of the population, potentially lowering the policy cost.

Solar Subsidy. A subsidy to solar, s^s, reduces the price of residential solar from p^s to $(1-s^s)p^s$. All households are eligible for the subsidy. The subsidy required to attain the emissions target equals 74 percent and the associated labor-income tax equals 5.4 percent.

The second column of Table 7 reports the aggregate effects of the solar subsidy. The subsidy increases residential solar energy production by more than a factor of five. In contrast to the clean-equipment subsidy, the solar subsidy leads to declines in both consumption and home production. The policy reduces disposable income by 5.4 percent (the size of the tax) for all households. However, only 38 percent of households use solar under the subsidy policy. For the 62 percent of households who do not use solar, the decline in disposable income is not offset by subsidy receipts. This negative income effect causes these households to reduce both consumption and home production, leading to the aggregate declines in Table 7.

The aggregate decrease in home production implies that households reduce both clean and dirty equipment. Clean equipment falls by more than dirty because the solar subsidy decreases the relative price of reducing emissions with solar compared to clean equipment, causing households to shift their expenditures on emissions reduction from clean equipment to solar.

The cost of the solar subsidy equals 5.4 percent of GDP, more than double the cost of the clean-equipment subsidy. This high cost stems from two factors: (1) solar is unattractive for some households (as captured by the taste shocks) and (2) solar capacity is limited by the size of the household's roof. The capacity constraints imply that achieving the emissions target requires widespread adoption of solar. Indeed, 38 percent of households adopt solar under the subsidy, up from just under 5 percent in the baseline. Such widespread adoption necessitates that some households for whom solar is relatively unattractive adopt. Incentivizing these households requires a larger subsidy, pushing the up the policy cost.

To see this result formally, we consider the cost of the solar subsidy when we re-calibrate the model so that households can install twice as much solar as in the current calibration, effectively relaxing the capacity constraints. In this case, achieving the emissions target only requires 23 percent of households to adopt solar, as opposed to 38 percent in the baseline calibration. The subsidy is also considerably smaller, equal to 49 percent instead of 74 percent. The policy costs 2.8 percent of GDP, approximately half of its cost in the baseline specification.

Cost-Minimizing Subsidy. We solve for the subsidy policy that minimizes the cost of attaining the emissions target. The policymaker chooses the level of the subsidy to clean equipment, the level of the subsidy to solar, the range of clean equipment to subsidize, and the range of household incomes that are eligible for the subsidies. As before, we require the subsidy to reduce household emissions by 10 percent and we finance the subsidy with a flat tax on labor income.

Table 8 summarizes the characteristics of the two simple policies and, in the third row, the cost-minimizing policy. The cost-minimizing policy includes a moderate income phase out; households in the bottom 80 percent of the income distribution are eligible and households in the top 20 percent are not. This phase out reflects the balance between targeting the most cost-effective households (the low-income households) and targeting the biggest emitters (the high-income, less-concerned households). The optimality of the income phase out depends critically on environmental preferences. Without environmental preferences, there are no cost-savings from targeting the subsidy to low-income households because all households have the same cutoff, $J_i^\star = p^c/(\phi(p^d + \mu p^e))\ \forall i$, implying that no single household is more cost-effective than another.

The income phase-out implies that the biggest emitters are not covered by the policy, and as a

Table 8: Policies that Attain the Emissions Target

	s^c (percent)	s^s (percent)	τ (percent)	Eligible tasks	Eligible HHs (income deciles)
Clean equipment	10	0	2.3	[0,1]	1-10
Solar	0	76	5.6	none	1-10
Cost-minimizing	19	0	0.88	[0.36, 0.66]	1-8

Note: The table summarizes the characteristics of three policies that attain the emissions target: a subsidy to all clean equipment (row 1), a subsidy to solar (row 2) and the cost-minimizing subsidy (row 3).

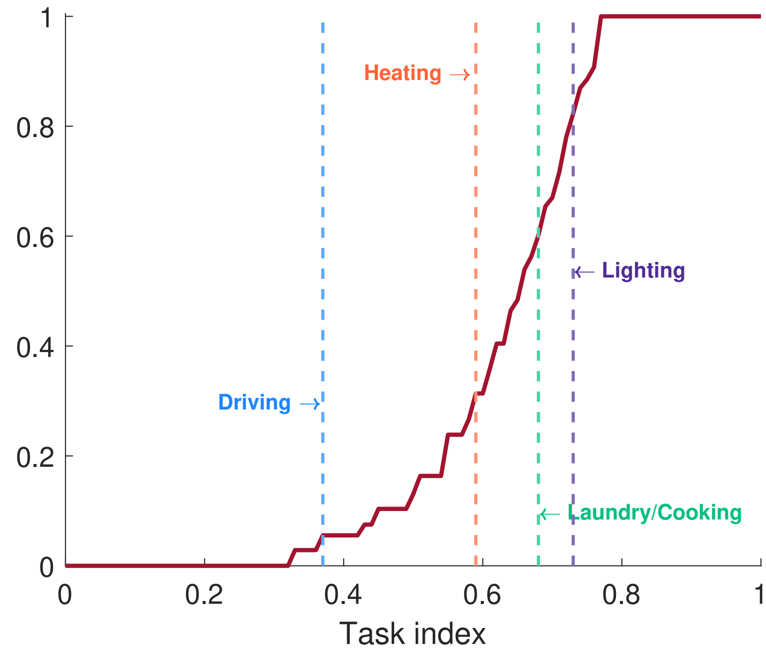
result, the policymaker needs to use a larger subsidy to attain the emissions target. The cost-minimizing clean-equipment subsidy is 19 percent, almost twice as big as the simple clean-equipment subsidy. Additionally, the cost-minimizing subsidy does not include a subsidy to solar. Subsidizing solar is more costly than subsidizing clean equipment because the subsidy must be large enough to overcome the effect of the taste shocks for any households that choose to adopt solar in response.

The cost-minimizing subsidy applies to clean equipment used for an intermediate range of tasks, ordered along the continuum between indices 0.36 and 0.66. This range balances the need to subsidize clean equipment with relatively high productivity with the need to subsidize clean equipment that households would not purchase without the subsidy. To help interpret this result, Figure 9 plots the fraction of households that use the clean equipment for each task in the baseline. Over the subsidized range of tasks, between 3 and 54 percent of households would use clean equipment without the subsidy.

It is useful to map the subsidized range of tasks to specific tasks and their associated clean equipment. While we do not observe the relative productivity of clean equipment for different tasks we do observe the level of adoption. The vertical lines in Figure 9 represent the placement of specific tasks, based on the empirical level of clean equipment adoption for that task. For example, five percent of households in our survey have electric vehicles (see Table 1). Since electric vehicles are a type of clean equipment used for driving, we place driving at the x-value where 5 percent of households use clean equipment for the task. Similarly, 85 percent of households use LED lights in RECS, and so we place, lighting, the associated task, farther to the right at the x-value where 85 percent of households use clean equipment for the task.

Figure 9 implies that heating and transport are within the subsidized range under the cost-minimizing subsidy, but laundry and cooking appliances and lighting are outside of the subsidized range. These results suggest that the least costly way for policymakers to attain the emissions target is to subsi-

Figure 9: Fraction of Households That Use Clean Equipment For Each Task



Note: The figure plots the fraction of households that use the clean technology for each task in the baseline. The vertical lines show where different tasks could lie along the continuum based on the fraction of households that use clean equipment for that task. The clean equipment associated with the driving, heating, laundry/cooking, and lighting tasks respectively are electric vehicles, heat pumps, energy-efficient laundry and cooking appliances, and LED bulbs.

dize electric vehicles and heat pumps, but subsidize not energy-efficient laundry or cooking appliances or LED lights.

The third column of Table 7 reports the aggregate effects of the cost-minimizing subsidy. Going straight to the last row reveals that there are large cost-savings from carefully designing household-focused climate policy. The cost of the cost-minimizing subsidy equals 0.8 percent of GDP, less than one third of the cost of the clean-equipment subsidy, and less than one sixth the cost of the solar subsidy.

To understand why the cost of the cost-minimizing subsidy is so much smaller than the clean-equipment subsidy, we decompose the impact of each subsidy on household emissions into three channels. The first channel is *technology substitution*. The subsidy reduces the relative price of clean equipment. In response, households use clean equipment for more tasks, as evident from the second row of Table 7. For example, the subsidy could cause a household to switch their heating equipment from a natural gas furnace to a heat pump.

The second channel is *task substitution*. The subsidy reduces the relative cost of the tasks the household produces with the clean technology, causing households to switch from dirty to clean technology tasks. Let $j_1 < J^\star$ and $j_2 > J^\star$ so that the household produces task j_1 with the dirty technology and task j_2 with the clean technology. The household's demand for task j_1 relative to task j_2 equals:

$$\frac{m_i(j_1)}{m_i(j_2)} = \left[\frac{(1-s^c)p^c}{\phi j_2(p^d + \mu p^e + \frac{\mu\theta_i}{\lambda_i})}\right]^{\varepsilon}.$$

An increase in the subsidy reduces the relative demand for the dirty-technology task. For example, if lighting is a clean task and driving is a dirty task, then the subsidy could cause households to do more lighting and less driving.

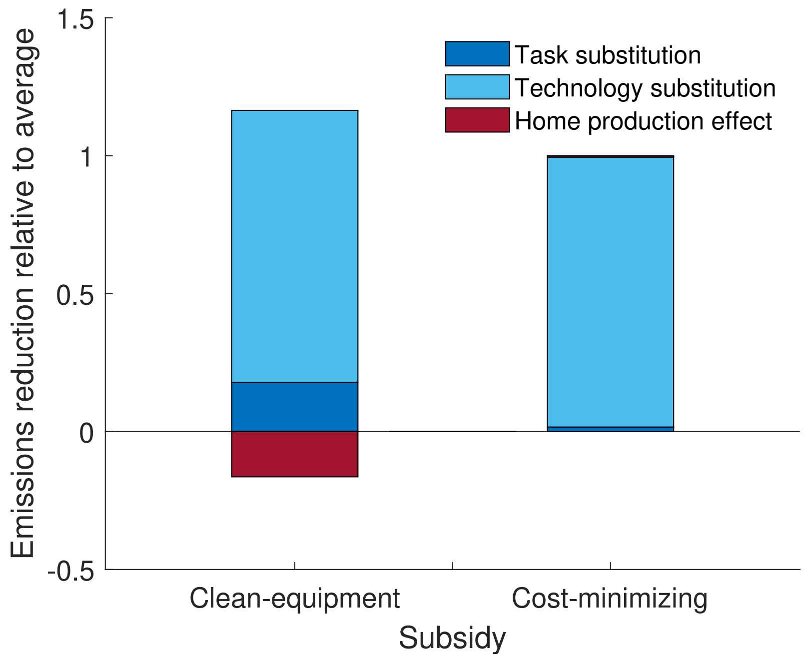
The third channel is the *home production effect*. The subsidy affects the relative price of home production, and the accompanying tax payments affect the household's disposable income. Both of these factors could cause households to adjust their level of home production and the associated energy demand, as evident from the fifth row of Table 7.

Figure 10 decomposes the emissions reduction under the clean-equipment subsidy (left bar) and under the cost-minimizing subsidy (right bar) into the task substitution, technology substitution, and home production effects. Under both policies, the majority of the emissions reduction is from technology substitution; task substitution is relatively minor in comparison. Returning to the earlier examples, the subsidy policies are more likely to incentivize the household to switch from a natural gas furnace (dirty equipment) to a heat pump (clean equipment) then they are to incentivize the household to do more lighting (if lighting is a clean task) and less driving (if driving is a dirty task).

The home production effect is negative under the clean-equipment subsidy, muting the reduction in emissions from the policy. This response is a form of rebound, a well-studied phenomenon in the environmental literature (see Gillingham, Rapson and Wagner (2016) for a review) in which households increase their use of an energy-using good following an improvement in energy efficiency. The intuition in our context is that the subsidy reduces the relative price of home production, causing households to increase home production (fifth row of Table 7) which, all else constant, increases emissions.

The decrease in the relative price of home production is stronger when the subsidy applies to more clean equipment that is inframarginal- in the sense that the household would have purchased the equipment in the absence of the subsidy. Consider a task, j_1, that the household produces with clean equipment under a subsidy, but with dirty equipment otherwise, and a task j_2 that the household produces with clean equipment regardless of whether there is a subsidy. The subsidy reduces the marginal cost of task j_2 by the size of the subsidy. In contrast, the subsidy reduces the marginal cost of task j_1 by less then the size of the subsidy because the household must incur the additional cost of using the clean technology instead of the dirty.

Figure 10: Decomposition of Household Emissions Reduction



Note: The figure decomposes the emissions reduction under the clean-equipment and cost-minimizing subsidies into three channels: (1) task substitution effect (dark blue), (2) technology substitution effect (light blue) and (3) home production effect (red).

Unlike under the clean-equipment subsidy, the home production effect actually leads to a slight increase in emissions reduction under the cost-minimizing policy. This difference in sign is due to two factors. First, the highest income households are not eligible for the subsidy, but they still pay higher taxes to finance the subsidy. Higher taxes without any subsidy receipts reduce their disposable income, causing them to reduce home production and emissions. Second, by targeting equipment with intermediate levels of adoption, the cost-minimizing policy subsidizes less inframarginal equipment. As a result, it leads to a smaller decrease in the relative price of home production, reducing rebound among households that do receive the subsidy. Consequently, aggregate home production falls by 0.1 percent (fifth row of Table 7), reducing emissions.

In sum, the cost-minimizing policy reduces the policy cost compared to the clean-equipment subsidy because both the income phase out and the targeted equipment range reduce rebound. The income phase out ensures that the households with the potential for the largest rebound (i.e., those with the most clean equipment in the baseline) are not eligible for the subsidy. The targeted equipment range avoids subsidizing equipment with high levels of adoption in the baseline, reducing rebound among the eligible households.

5.3. Changes in Public Concern for Climate Change

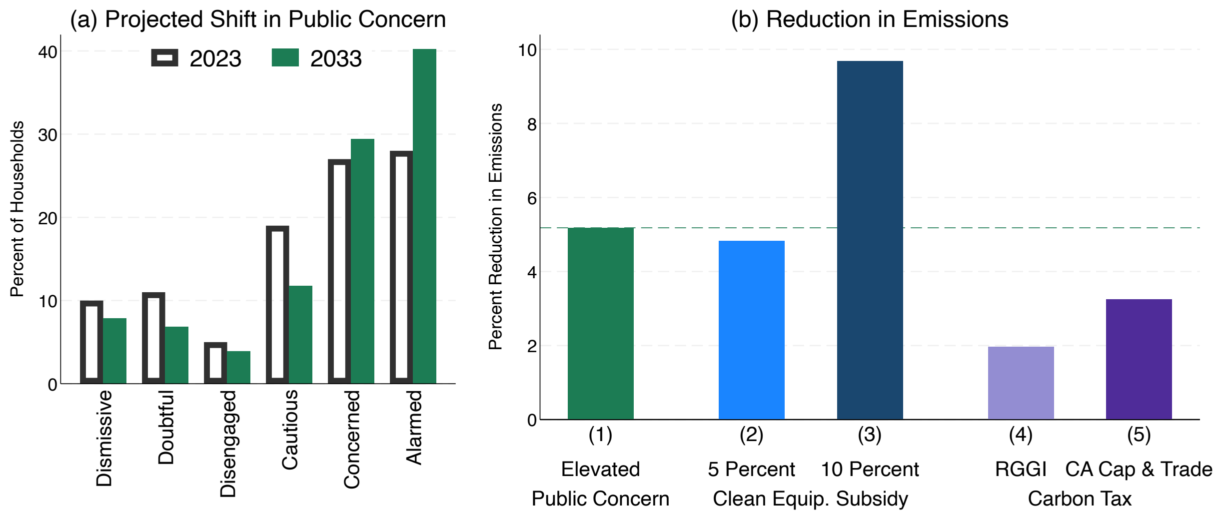
The analysis from our survey and model highlight that a household's level of climate concern is a quantitatively important determinant of their emissions. This result raises the possibility that changes in public attitudes towards climate change, absent any climate policy, could have meaningful effects on aggregate household emissions. Results from the CCAM project suggest that Americans' climate concern has generally increased over the past decade. For example, the fraction of households who are more concerned (i.e., those who are either concerned or alarmed) increased from 39 to 55 percent from 2013 to 2023 (see Appendix Figure C1). This trend could be due to changes in information, experiences, or beliefs, all of which would manifest as a change in environmental preferences in our model.

We explore the aggregate impact on household emissions if the historical trends in climate change concern continue going forward. Panel a of Figure 11 plots our predicted distribution of climate concern in 2033 when we assume that the change in the fraction of the population in each group over the next ten years is the same as the change from the past ten years. We find that the elevated climate concern in 2033 reduces household emissions by 5.2 percent relative to our baseline specification, as shown by bar (1) in panel b of Figure 11. The mechanisms underlying this emissions reduction mirror those from the subsidy policies; elevated climate concern causes households to increase clean equipment and solar energy and to decrease dirty equipment. To put this emissions impact in perspective, bars (2) and (3) show the decrease in household emissions from 5 and 10 percent subsidies to clean equipment, respectively. The emissions reduction from elevated climate concern is equivalent to a clean equipment subsidy in between these two values, equal to 5.4 percent.

We compare the emissions impact of elevated climate concern to the emissions impact from a carbon price. Two of the largest carbon pricing programs in the U.S. are the California Cap and Trade Program and the Regional Greenhouse Gas Initiative (RGGI). Bars (4) and (5) plot the decrease in household emissions from carbon prices equal to the 2024 average under RGGI, 21 dollars per ton, and under the California Cap and Trade Program, 35 dollars per ton. The predicted decrease in household emissions from either carbon price is smaller than the reduction from elevated climate concern. The emissions impact from from elevated climate concern is equivalent to a 57 dollar per ton carbon price, more than double the RGGI price and more than 50 percent higher than the California Cap and Trade price.

We focused on a realistic near-term change in climate concern based on the historical trends. Alternatively, we could consider a more extreme shift in which everyone becomes alarmed (the highest level of climate concern). Such a dramatic increase in climate concern would reduce household

Figure 11: Reduction in Emissions from Counterfactual Distribution of Climate Concern



Note: Panel (a) plots the baseline distribution of climate change concern (black boxes) and a projection of the 2033 distribution (green filled) based on the observed change in concern between 2013 and 2023 in the CCAM data. Panel (b) plots the percent reduction in emissions in several scenarios: (1) the projected shift in public concern from panel (a), (2) a subsidy on clean equipment of 5 percent, (3) a subsidy on clean equipment of 10 percent, (4) a carbon tax equivalent in size to the Regional Greenhouse Gas Initiative (RGGI), and (5) a carbon tax equivalent in size to the California Cap and Trade Program.

emissions by 23 percent, equivalent to a 24 percent subsidy to clean equipment. It is also possible that public concern for climate change could decrease over time instead of increase, pushing up household emissions. For example, our model predicts that if climate concern returns to its 2013 distribution, then household emissions would increase by 4.8 percent. In the extreme, if everyone becomes dismissive of climate change (the lowest level of concern), then household emissions would increase by 65 percent.

Taken as a whole, these results highlight that shifts in climate concern can meaningfully impact household emissions, absent any specific climate policy. Simply extrapolating the historical trend in climate concern forward ten years leads to a 5.2 percent reduction in household emissions, equivalent to what one would achieve under a 5.4 percent subsidy to clean equipment or a 57 dollar per ton carbon tax. Thus, accounting for environmental preferences and their impact on household decisions is important for understanding households' emissions-related decisions and, ultimately, for designing household-focused climate policy.

6. Conclusion

Emissions from households' direct use of energy account for approximately one third of U.S. emissions in the aggregate. This paper develops a new model of home production and household energy use to study the determinants of household emissions and how they respond to climate policies and to shifts in public attitudes towards climate change. Household emissions in the model result from a set of home production tasks involving either clean or dirty varieties of equipment. Additionally, households have heterogeneous distaste for their own carbon emissions. Using a new survey, we document that such environmental preferences exist, vary across households, are correlated with households' clean equipment decisions, but are uncorrelated with household income.

We use the model to study the most cost-effective approach to designing climate subsidies for households, such as those included in the IRA and in many state and local programs. We find that such subsidies should target a range of clean equipment with intermediate levels of adoption, and should phase out for the highest income households. Both of these features reduce the amount of inframarginal clean equipment covered by the subsidy, leading to less rebound and greater emissions reduction. We also use the model to predict how future changes in environmental preferences could impact emissions. We find that if climate concern increases over the next decade by the same amount as in the past decade, household emissions will fall by 5 percent, the same decrease as our model predicts from a 57 dollar per ton carbon tax.

A unique feature of our study is that we focus specifically on the emissions from household energy use, as opposed to the emissions from firm energy use. Households are similar to firms, in that they produce home production using equipment and energy, and they can choose equipment with varying degrees of energy efficiency. However, households also differ critically from firms in that they have preferences for consumption, home production, and importantly in our context, for the environment. Indeed, we show that changes in these preferences alone can have substantial emissions effects absent any policy.

References

Acemoglu, Daron and Pascual Restrepo, "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, 2019, *33* (2), 3–30.

_ , Philippe Aghion, Leonardo Bursztyn, and David Hémous, "The Environment and Directed Technical Change," *American Economic Review*, 2012, *102* (1), 131–166.

Aghion, Philippe, David Hémous, Lint Barrage, and Ernest Liu, "Transition to Green Technology along the Supply Chain," 2024. Unpublished Manuscript, LSE.

_ , Roland Bénabou, Ralf Martin, and Alexandra Roulet, "Environmental Preferences and Technological Choices: Is Market Competition Clean or Dirty?," *American Economic Review: Insights*, 2023, *5* (1), 1–20.

Anderson, Soren and A Justin Kirkpatrick, "Distributional Consequences of Policies for Electric Heat Conversion," *Journal of the Association of Environmental and Resource Economists*, forthcoming.

Andreoni, James, "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving," *Economic Journal*, 1990, *100* (401), 464–477.

Arkolakis, Costas and Conor Walsh, "Clean Growth," *NBER Working paper 31615*, 2023.

Aruoba, S. Borağan, Morris A. Davis, and Randall Wright, "Homework in Monetary Economics: Inflation, Home Production, and the Production of Homes," *Review of Economic Dynamics*, 2016, *21*, 105–124.

Barrage, Lint and William Nordhaus, "Policies, Projections, and the Social Cost of Carbon: Results from the DICE-2023 model," *Proceedings of the National Academy of Sciences*, 2024, *121* (13), e2312030121.

Becker, Gary S, "A Theory of the Allocation of Time," *The Economic Journal*, 1965, *75* (299), 493–517.

Benhabib, Jess, Richard Rogerson, and Randall Wright, "Homework in Macroeconomics: Household Production and Aggregate Fluctuations," *Journal of Political Economy*, December 1991, *99* (6), 1166–1187.

Bistline, John, Neil R. Mehrotra, and Catherine Wolfram, "Economic Implications of the Climate Provisions of the Inflation Reduction Act," *Brookings Papers on Economic Activity*, March 2023. BPEA Spring 2023.

Boerma, Job and Loukas Karabarbounis, "Inferring Inequality With Home Production," *Econometrica*, 2021, *89* (5), 2517–2556.

Borenstein, Severin and Lucas W Davis, "The Distributional Effects of U.S. Clean Energy Tax Credits," *Tax Policy and the Economy*, 2016, *30* (1), 191–234.

Casey, Gregory, Woongchan Jeon, and Christian Traeger, "The Macroeconomics of Clean Energy Subsidies," *CESifo Working Paper 10828*, 2023.

Chan, Nathan W, "Pigouvian Policies under Behavioral Motives," *Journal of the Association of Environmental and Resource Economists*, 2024, *11* (1), 97–135.

Chryst, Breanne, Jennifer Marlon, Sander van der Linden, Anthony Leiserowitz, Edward Maibach, and Connie Roser-Renouf, "Global Warming's "Six Americas Short Survey": Audience Segmentation of Climate Change Views Using a Four Question Instrument," *Environmental Communication*, 2018, *12* (8), 1109–1122.

Colas, Mark and Emmett Saulnier, "Optimal Subsidies for Residential Solar," *Journal of Political Economy: Microeconomics*, forthcoming.

Costello, Christopher and Matthew Kotchen, "Policy Instrument Choice with Coasean Provision of Public Goods," *Journal of the Association of Environmental and Resource Economists*, 2022, *9* (5), 947–980.

Cruz, José-Luis and Esteban Rossi-Hansberg, "The Economic Geography of Global Warming," *Review of Economic Studies*, 2024, *91* (2), 899–939.

Davis, Lucas W, "The Economic Determinants of Heat Pump Adoption," *Environmental and Energy Policy and the Economy*, 2024, *5.*

_ , Alan Fuchs, and Paul Gertler, "Cash for Coolers: Evaluating a Large-Scale Appliance Replacement Program in Mexico," *American Economic Journal: Economic Policy*, 2014, *6* (4), 207–238.

Dorsey, Jackson and Derek C. Wolfson, "Unequal Uptake: Assessing Distributional Disparities in the Residential Solar Market," August 2024. NBER Working Paper 32814.

Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram, "Do Energy Efficiency Investments Deliver? Evidence from the Weatherization Assistance Program," *Quarterly Journal of Economics*, 2018, *133* (3), 1597–1644.

Fried, Stephie, Kevin Novan, and William B Peterman, "The Distributional Effects of a Carbon Tax on Current and Future Generations," *Review of Economic Dynamics*, 2018, *30*, 30–46.

_ , _ , and _ , "Understanding the Inequality and Welfare Impacts of Carbon Tax Policies," *Journal of the Association of Environmental and Resource Economists*, 2024, *11* (S1), S231–S260.

Gillingham, Kenneth, David Rapson, and Gernot Wagner, "The Rebound Effect and Energy Efficiency Policy," *Review of Environmental Economics and Policy*, 2016.

Golosov, Mikhail, John Hassler, Per Krusell, and Aleh Tsyvinski, "Optimal Taxes on Fossil Fuel in General Equilibrium," *Econometrica*, 2014, *82* (1), 41–88.

Greenwood, Jeremy, Ananth Seshadri, and Mehmet Yorukoglu, "Engines of Liberation," *Review of Economic Studies*, 2005, *79* (1), 109–133.

__, Richard Rogerson, and Randall Wright, "Putting Home Economics Into Macroeconomics," *Federal Reserve Bank of Minneapolis Quarterly Review*, 1993, *17* (3).

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, "Time Varying Risk Aversion," *Journal of Financial Economics*, 2018, *128* (3), 403–421.

Hassler, John, Per Krusell, Conny Olovsson, and Michael Reiter, "On the Effectiveness of Climate Policies," *IIES WP*, 2020, *53*, 54.

Hinkelmann, Stefan, "Green Subsidies, the Energy Transition, and Implications of the Inflation Reduction Act," 2024. Unpublished Working Paper.

Howden, Wesley, Remy Levin, and Meng Song, "The Global Impacts of Climate Change on Risk Preferences," *Available at SSRN 4132517*, 2022.

Humlum, Anders, "Robot Adoption and Labor Market Dynamics," *Working paper*, 2021.

Känzig, Diego R., "The Unequal Economic Consequences of Carbon Pricing," 2024. Unpublished Manuscript, Northwestern University.

Kuhn, Moritz and Lennard Schlattmann, "Distributional Consequences of Climate Policies," *Working paper*, 2024.

Labandeira, Xavier, Jose M. Labeagac, and Xiral Lopez-Otero, "A Meta-Analysis on the Price Elasticity of Energy Demand," *Energy Policy*, 2017, *102*, 549—568.

Leiserowitz, A, E Maibach, Rosenthal, S, Kotcher, J, Goddard, E, Carman, J, Verner, M, Ballew, M, Marlon, J, Lee, S, Myers, T, Goldberg, M, Badullovich, N, and Thier, K, "Global Warming's Six Americas, Fall 2023," *Yale University and George Mason University. New Haven, CT: Yale Program on Climate Change Communication.*, 2023.

Levin, Remy and Daniela Vidart, "Risk-Taking Adaptation to Macroeconomic Experiences," *working paper*, 2023.

Maibach, Edward W., Anthony Leiserowitz, Connie Roser-Renouf, and C. K. Mertz, "Identifying Like-Minded Audiences for Global Warming Public Engagement Campaigns: An Audience Segmentation Analysis and Tool Development," *PLOS ONE*, March 2011, *6* (3), e17571.

Malmendier, Ulrike and Stefan Nagel, "Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?," *Quarterly Journal of Economics*, 2011, *126* (1), 373–416.

McGrattan, Ellen R., Richard Rogerson, and Randall Wright, "An Equilibrium Model of the Business Cycle with Household Production and Fiscal Policy," *International Economic Review*, 1997, *38* (2), 267–290.

Muehlegger, Erich and David S Rapson, "Subsidizing Low-and Middle-Income Adoption of Electric Vehicles: Quasi-Experimental Evidence from California," *Journal of Public Economics*, 2022, *216*, 104752.

Newell, Richard G, William A Pizer, and Daniel Raimi, “US Federal Government Subsidies for Clean Energy: Design Choices and Implications,” *Energy Economics*, 2019, *80*, 831–841.

Olovsson, Conny, “Optimal Taxation with Home Production,” *Journal of Monetary Economics*, 2015, *70*, 39–50.

Parente, Stephen L., Richard Rogerson, and Randall Wright, “Homework in Development Economics: Household Production and the Wealth of Nations,” *Journal of Political Economy*, August 2000, *108* (4), 680–687.

Rogerson, Richard, “Structural Transformation and the Deterioration of European Labor Market Outcomes,” *Journal of Political Economy*, 2008, *116* (2), 235–259.

Rupert, Peter, Richard Rogerson, and Randall Wright, “Homework in Labor Economics: Household Production and Intertemporal Substitution,” *Journal of Monetary Economics*, 2000, *46* (3), 557–579.

Shojaeddini, Ensieh and Ben Gilbert, “Heterogeneity in the Rebound Effect: Evidence from Efficient Lighting Subsidies,” *Environmental and Resource Economics*, 2023, *84* (1), 173–217.

Stock, James H., “Climate Change, Climate Policy, and Economic Growth,” *NBER Macroeconomics Annual*, 2019, *34*, 39–50.

U.S. Department of Transportation, “Summary of Travel Trends, 2022 National Househld Travel Survey,” Technical Report, Federal Highway Administration 2022.

Wichman, Casey J, “Incentives, Green Preferences, and Private Provision of Impure Public Goods,” *Journal of Environmental Economics and Management*, 2016, *79*, 208–220.

Zivin, Joshua Graff and Kevin Novan, “Upgrading Efficiency and Behavior: Electricity Savings from Residential Weatherization Programs,” *The Energy Journal*, 2016, *37* (4), 1–24.

Appendix: For Online Publication Only

A. Stylized Facts

We restrict our analysis in all samples (CEX, RECS, our survey) to people between the ages of 20 (to limit the effect of students) and 84 (the 99th percentile of the age distribution in our survey). We drop all households with quarterly expenditures less than zero from the CEX.

A.1. Household Energy and Emissions Shares

We calculate household energy consumption and carbon emissions from the EIA data. We describe the process for energy consumption. The process for carbon emissions is analogous. The EIA divides energy use into four categories, residential, transportation, commercial, and industrial. Residential energy use includes all energy used by households at their residence. The transportation sector energy consumption includes all energy used by vehicles. Household energy consumption in our model equals residential energy consumption plus a portion of transportation energy consumption.

We take the following steps to determine the fraction of transportation energy from households. First, we calculate the fraction of petroleum use in the transportation sector that is attributable to light-duty vehicles and motorcycles. Next, we calculate the portion of light-duty and motorcycle vehicle miles traveled (VMT) that are attributable to households. Given these two fractions, we use the following formula to calculate household transportation energy use:

$$\text{HH trans energy} = \frac{\text{light-duty vehicle petroleum}}{\text{trans petroleum}} \times \frac{\text{HH VMT}}{\text{light-duty vehicle VMT}} \times \text{trans petroleum} \tag{9}$$

This calculation assumes that all household transportation energy use is from petroleum used for light-duty vehicles and motorcycles.

We describe how to calculate each fraction in equation (9). Data on the fraction of transportation petroleum used by light duty vehicles and motorcycles is from the National Highway Statistics Tables and data on petroleum use by light duty vehicles and motorcycles and on total petroleum use for all transportation is from Table 4-6 from the National Highway Statistics.[16]

Data on average household VMT is from Table 3.4 of the National Household Survey (U.S. Department of Transportation, 2022). The data report household VMT for years 1983, 1990, 1995, 2001, 2009, 2017, and 2022. The data after 2009 include self-reported and network calculated distance traveled. The data prior to 2009 only include self-reported distance. We adjust the pre-2009 data based on the average fraction of self-reported to network calculated distance post 2009.

Data on the number of households is from the U.S. Census Bureau, retrieved from FRED, Federal Reserve Bank of St. Louis, (series TTLHH). Household VMT equals average household VMT multiplied by the number of households.

[16]The data can be downloaded from: www.bts.gov/content/energy-consumption-mode-transportation.

Total light-duty vehicle VMT is the sum of short- and long-wheel base light duty vehicle VMT. The data is from the Bureau of Transportation statistics.[17]

A.2. Survey Design

We introduced the survey to respondents as being about "energy-saving investments at home." In the first section of the survey, we asked households if they owned or leased several types of equipment. For equipment which they did not own/lease, we asked if they had considered purchasing/leasing it.

We included the following types of equipment:

- Electric vehicles (including all-electric and plug-in hybrids)
- Non-plug-in (NPI) hybrid vehicles
- Home solar panels
- Heat pump heating and cooling
- Energy efficient appliances
  - Energy efficient appliances include Energy Star certified refrigerator, clothes washer or dryer, dishwasher, electric or induction range, stove, or oven.
- Home weatherization or insulation
  - Costing more than $1000

We only asked homeowners about solar panels, heat pumps, energy efficient appliances and weatherization/insulation. We asked all households about electric and NPI hybrid vehicles. For solar panels and heat pumps, we asked homeowners to report if these items were present when they purchased the home.

In the second section, we asked respondents why they owned/leased each type of clean equipment that they owned/leased and why they considered owning/leasing each type of equipment that they had considered. Respondents were given different factors and asked to rank up to three of them in order of importance. We randomized the order in which the factors appeared, with "other" always appearing last.

We included the following factors for all types of clean equipment:

- Reducing carbon emissions
- Reducing [energy; fuel] costs

[17] The data can be downloaded from: www.bts.gov/content/light-duty-vehicle-short-wheel-base-and-motorcycle-fuel-consumption-and-travel and www.bts.gov/content/other-2-axle-4-tire-vehicle-fuel-consumption-and-travel.

- Tax credits and rebates
- Other: *please specify*

For solar panels, energy efficient appliances, and weatherization/insulation, we also included

- Increasing the value of my home

For electric vehicles and hybrids, we included

- Performance, quiet, safety

We also asked respondents why they did *not* own/lease/consider certain types of equipment. Again they were given several factors to rank, which appeared in a randomized order. The factors were the following:

- It is too expensive / There are not enough tax credits
- I plan to [own/lease; install] _____ soon
- Other: *please specify*

For electric vehicles and hybrid vehicles:

- I don't drive / I don't need a car / I don't need a new car

For electric vehicles and plug-in hybrids:

- There is no place to plug it in at my home / I'm not confident about charger network
- The electrical grid still produces a lot of carbon emissions

For NPI Hybrids only:

- Hybrid cars are still gasoline powered

For solar panels

- It is not feasible at my house/on my roof
- The utility company does not pay enough for excess solar generation

For heat pumps; energy-efficient appliances or weatherization/insulation

- My [heating/cooling; appliances/insulation] do not need to be replaced.
- I do not have control over decisions about [the heating/cooling system at; to make energy saving investments on] my home.

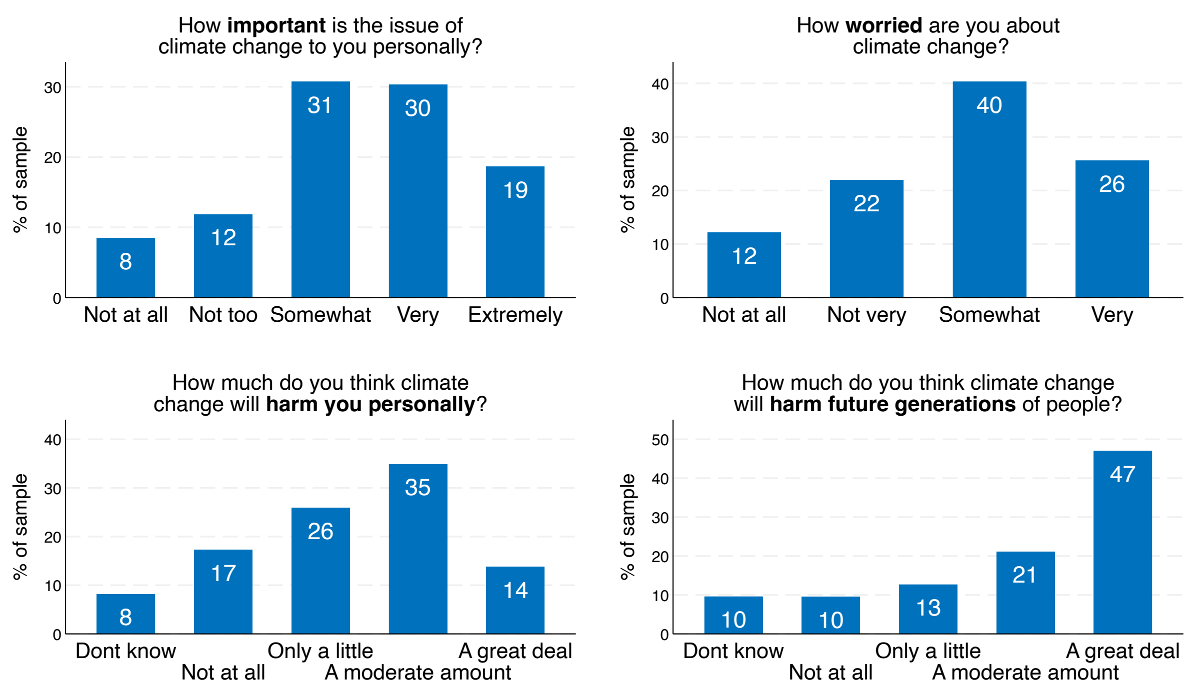
The survey code book can be accessed at https://uasdata.usc.edu/index.php

A.3. The Six Americas Classification Method

The Yale Program on Climate Change Communications and George Mason University Center for Climate Change Communications have run a series of nationally representative surveys about climate change perceptions since 2008, called the Climate Change and the American Mind (CCAM) project. Maibach et al. (2011) used latent class analysis of the data on 36 questions from these surveys to develop a segmentation of the population into six groups who perceive and respond to climate change in distinct ways. The six segments minimized the variance within group while maximizing variance between groups. The resulting classification method essentially uses a multinomial logit regression to assign group membership based on answers to certain questions.

Chryst et al. (2018) ask respondents four questions about their views on climate change (see figure A1) and use the answers to divide respondents into six groups, with concern levels ranging from dismissive of climate change to alarmed. The coefficients necessary to assign groups with data from the Short Survey are available in Table 2 of Chryst et al. (2018). A convenient group scoring tool is also available on the Yale Climate Communications website.[18]

Figure A1: Six Americas Short Survey

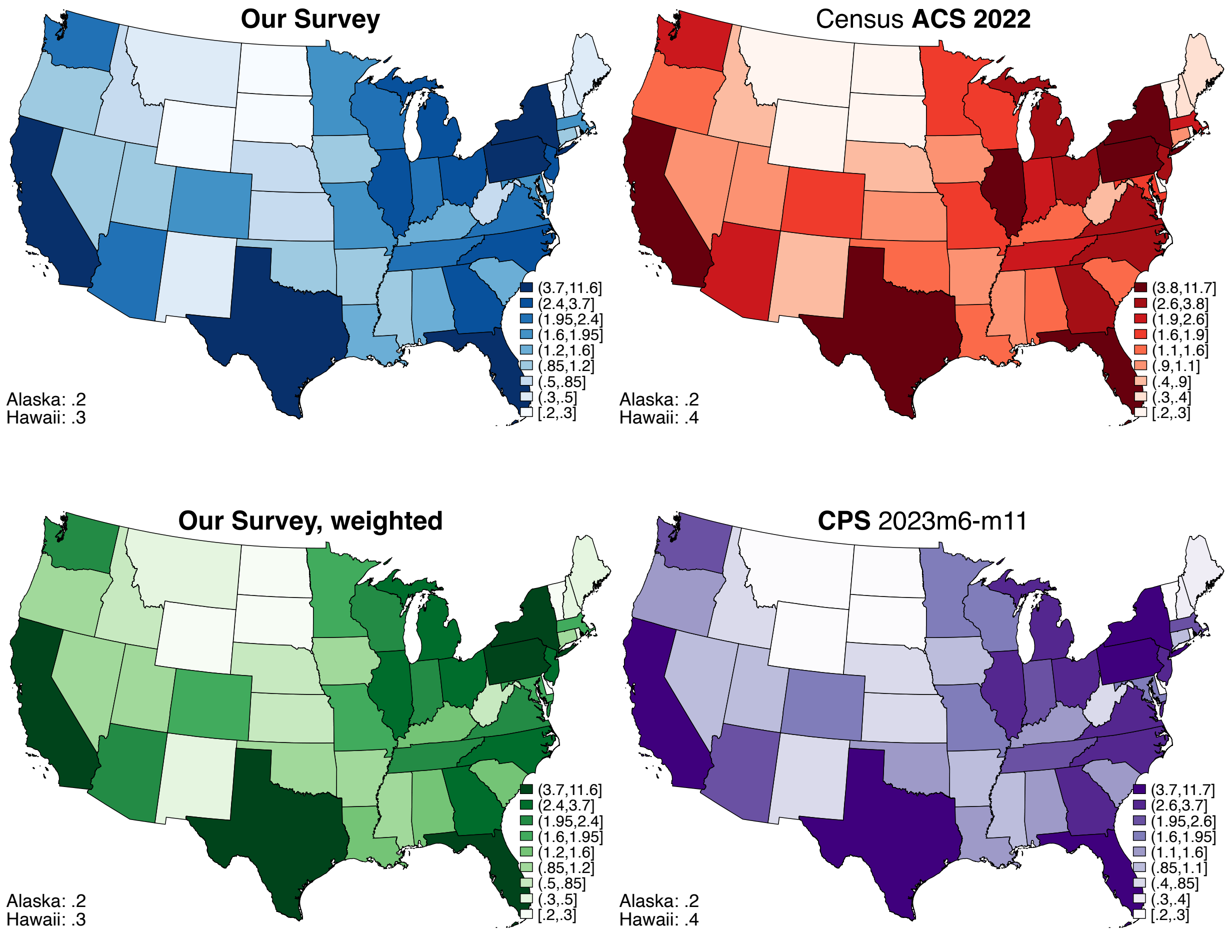


Note: This figure plots the distribution in our sample of responses to each of the questions in the Six Americas Short Survey from Chryst et al. (2018). In all cases we replaced the phrase "global warming" with "climate change".

A.4. Additional tables and figures

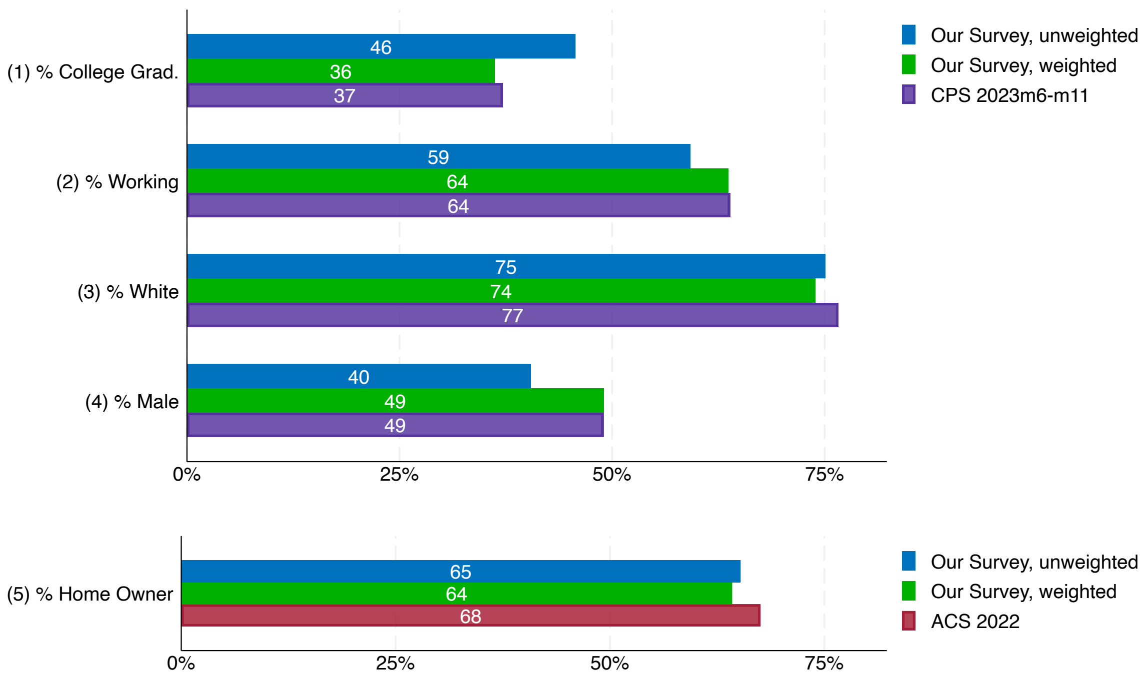
[18] https://climatecommunication.yale.edu/visualizations-data/sassy/

Figure A2: Geographic Balance



Note: This figure plots the share of our sample, the 2022 ACS, and 2023m6-m11 CPS residing in each state. In green our survey data is weighted by weights calibrated to ensure that our sample precisely matches the CPS distributions of age, education, gender, income, race, region.

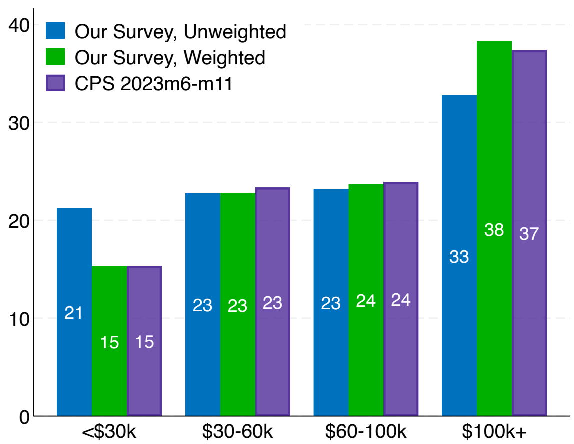
Figure A3: Demographic Balance



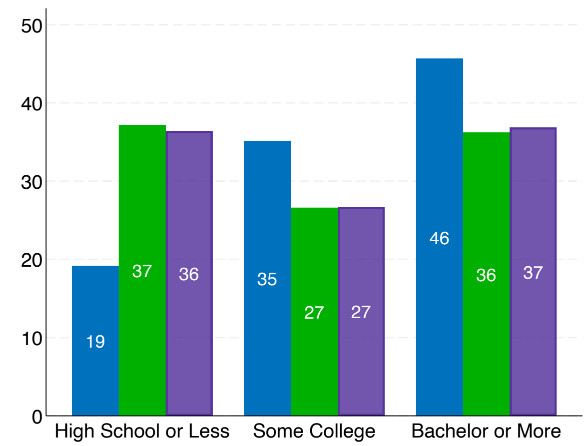
Note: This figure plots summary statistics for our sample (blue), 2023m6-m11 CPS (purple), and 2022 ACS (red).

Figure A4

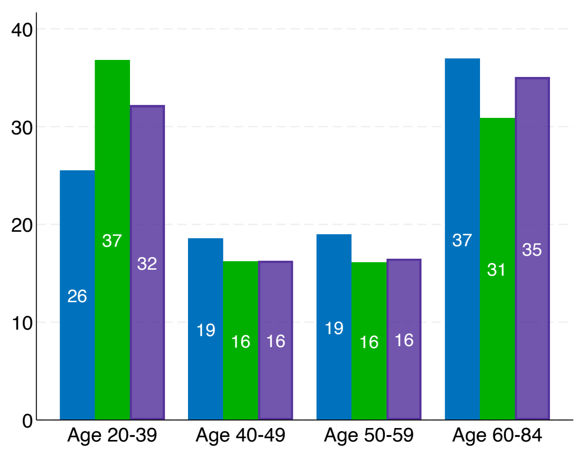
(a) Income Distribution



(b) Education Distribution



(c) Age Distribution



Note: This figure plots the distribution of income (a), education (b), and age (c) in our sample (blue), the CPS (purple), and our sample weighted with weights calibrated to match the CPS (green).

Table A1: Comparison to Other Data

	Income	Age	Home Owner	Electric Veh.	Solar Panels	Heat Pumps
2020 RECS	$60-75k	53	67%	1.5 %	4.6%	14.4%
2020 CEX	$40-50k	51	66%	0.7%	3.3%	
2023 CEX	$60-75k	51	65%	2.2%	5.7%	
2024 Our Survey	$60-75k	52	65%	4.9%	7.5%	27.9%
2024 Our Survey, Weighted	$75-100k	49	64%	5.5%	8.1%	29.3%

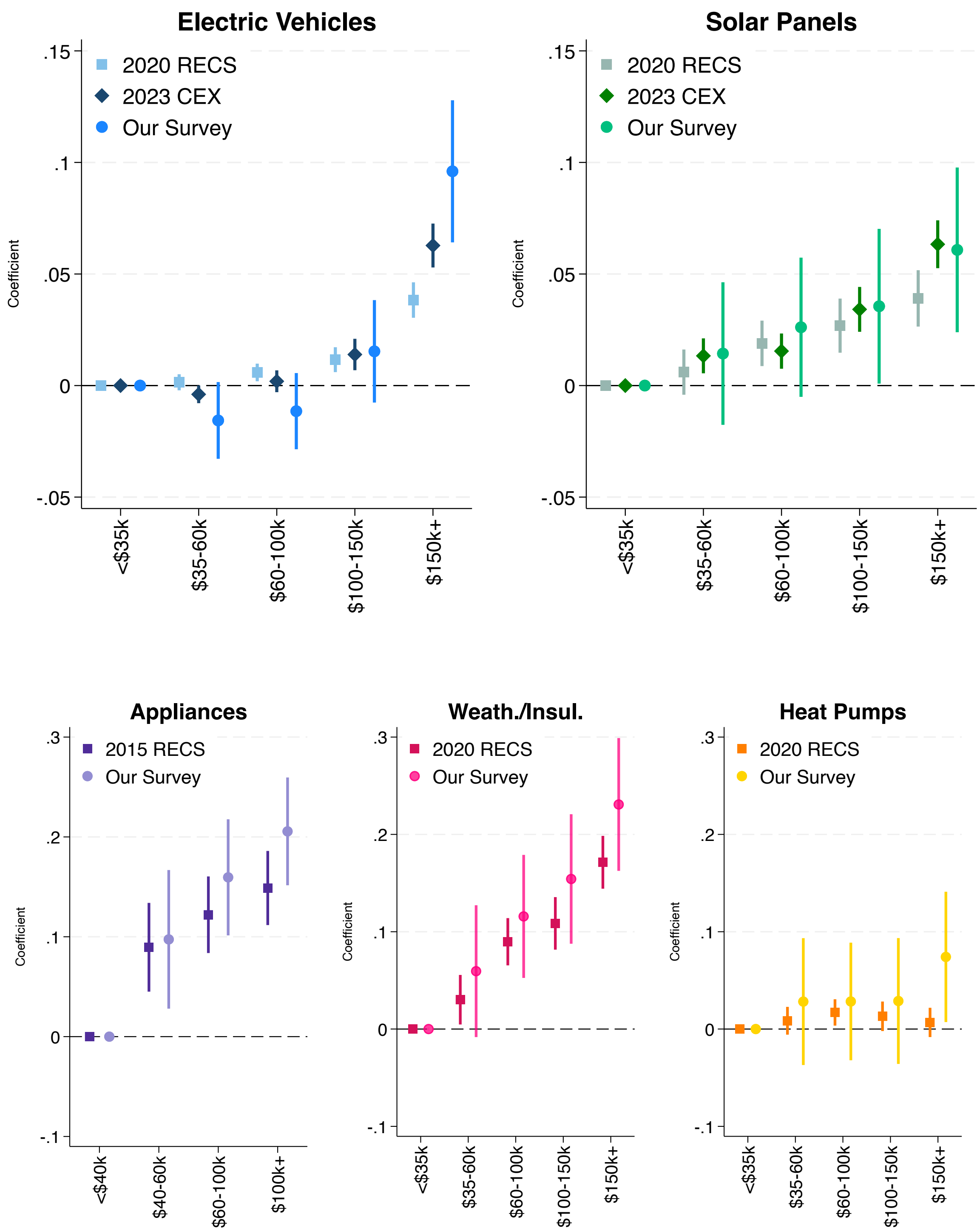
Note: This table reports summary statistics in our sample, the 2020 RECS, and 2020 and 2023 CEX. Income is median income. Age is average age. For solar panels and heat pumps we restrict to home owners in both samples for comparability. RECS and CEX are weighted.

Table A2: Percent of Households with Clean Equipment and Solar

	Drivers		Single Family Home		
%	Electric Veh.	Hybrid (NPI)	Solar Panels	Solar Panels	Heat Pumps
Own/Lease	7	18	9	8	29
Considered	32	33	49	46	16
Installed			8	7	10

Note: The table reports the fractions of households that own/lease each type of clean equipment (first row), considered purchasing (second row), or installed equipment themselves, rather than buying a house at which they were already installed (third row). Columns (1)-(3) have sample restrictions which differ from Table 1. In columns (1)-(2) we drop households who reported that they don't drive or don't need a car. In columns (3) we restrict to home owners with a single family home.

Figure A5: Variation in Clean Equipment with Household Income



Note: The figure plots the coefficients for the income fixed effects in equation (1) run in the 2020 RECS (squares), 2023 CEX (diamonds), and our sample (circles), as well as 95 percent confidence intervals. Engery-efficient appliances are defined in the 2015 RECS as appliances that are Energy Star certified (which is not available in the 2020 survey). Weatherization/insulation is defined in the 2020 RECS as having the highest insulation level, “well insulated”.

Table A3: Households Ranking Each Factor as First or Second Most Important

(a) Own/Lease

%	Electric Veh. (u)	Electric Veh. (w)	Hybrid (NPI) (u)	Hybrid (NPI) (w)	Solar Panels (u)	Solar Panels (w)	Heat Pumps (u)	Heat Pumps (w)	Appl./Weath. (u)	Appl./Weath. (w)
(1) Reduce carbon emissions	44	39	35	33	27	25	17	16	23	20
(2) Reduce fuel costs	70	66	75	76						
energy costs					91	91	87	83	89	88
(3) Tax credits and rebates	33	31	27	28	44	42	22	23	25	25
(4) Performance, quiet, safety	39	41	47	49						
Raise home value					26	32	48	49	50	54
(5) Other	6	12	7	7	5	3	17	18	5	5
N	156		470		131		187		1718	

(b) Considered

%	Electric Veh. (u)	Electric Veh. (w)	Hybrid (NPI) (u)	Hybrid (NPI) (w)	Solar Panels (u)	Solar Panels (w)	Heat Pumps (u)	Heat Pumps (w)	Appl./Weath. (u)	Appl./Weath. (w)
(1) Reduce carbon emissions	53	47	34	31	28	26	28	26	26	24
(2) Reducing fuel costs	81	83	90	87						
energy costs					95	94	87	84	87	85
(3) Tax credits and rebates	25	27	21	22	37	37	23	28	28	28
(4) Performance, quiet, safety	35	36	41	43						
Raise home value					32	35	43	42	37	42
(5) Other	4	4	3	2	3	3	7	8	5	4
N	1009		224		875		223		94	

Note: The table reports the fraction of households that ranked each factor (row) as either first or second most important for their decision to purchase (panel a) or consider (panel b) a given type of equipment. Raw fractions are reported in (u) columns, weighted fractions are reported in (w) columns. Weights are calibrated with iterative proportional fitting so that our sample precisely matches the CPS distributions of age, education, gender, income, race, region.

Table A4: Percent Ranking Carbon Emissions as Important
Probit, Marginal Effects

	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
$150k+	0.035	0.037	0.044	0.032
	(0.025)	(0.025)	(0.035)	(0.036)
$100-150k	-0.012	-0.010	-0.023	-0.026
	(0.023)	(0.023)	(0.034)	(0.034)
$60-100k	-0.031	-0.029	-0.048	-0.051
	(0.021)	(0.021)	(0.032)	(0.032)
$35-60k	-0.023	-0.022	-0.035	-0.036
	(0.023)	(0.023)	(0.035)	(0.036)
Controls: Age, Region		✓		✓
Observations	2019	2019	2019	2019

Note: The table reports probit marginal effects from an analogous specification to equation (2) where Y_i is an indicator for whether household i ranked reducing carbon emissions the most important (columns 1 and 2), or either first or second important (columns 3 and 4) factor in their decision to purchase at least one type of clean equipment. Table 3 reports the equivalent linear probability model. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A5: Percent Ranking Carbon Emissions as Important
Weighted Linear Probability Model

	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
$150k+	0.026	0.037	0.006	0.002
	(0.032)	(0.033)	(0.047)	(0.048)
$100-150k	-0.010	-0.002	-0.030	-0.030
	(0.030)	(0.031)	(0.046)	(0.047)
$60-100k	-0.046	-0.039	-0.071	-0.072
	(0.028)	(0.029)	(0.045)	(0.045)
$35-60k	-0.041	-0.036	-0.026	-0.029
	(0.030)	(0.030)	(0.051)	(0.051)
Controls: Age, Region		✓		✓
Observations	2019	2019	2019	2019

Note: The table reports the weighted version of Table 3. That is, results from equation (2) where Y_i is an indicator for whether household i ranked reducing carbon emissions the most important (columns 1 and 2), or either first or second important (columns 3 and 4) factor in their decision to purchase at least one type of clean equipment. Weights are calibrated with iterative proportional fitting so that our sample precisely matches the CPS distributions of age, education, gender, income, race, region. Table 3 reports the unweighted version. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A6: Percent Ranking Carbon Emissions as Important Considered Equipment

	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
\$150k+	0.010	0.008	0.050	0.050
	(0.031)	(0.032)	(0.038)	(0.039)
\$100-150k	-0.026	-0.027	-0.050	-0.051
	(0.031)	(0.031)	(0.038)	(0.038)
\$60-100k	-0.028	-0.029	-0.013	-0.016
	(0.029)	(0.029)	(0.037)	(0.036)
\$35-60k	-0.017	-0.016	-0.021	-0.021
	(0.032)	(0.032)	(0.039)	(0.039)
Controls: Age, Region		✓		✓
Observations	1768	1768	1768	1768

Note: The table reports the results from equation (2) where Y_i is an indicator for whether household i ranked reducing carbon emissions the most important (columns 1 and 2), or either first or second important (columns 3 and 4) factor in their consideration of at least one type of clean equipment. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A7: Percent "More Concerned" About Climate Change

	(1)	(2)
\$150k+	0.036	0.027
	(0.028)	(0.028)
\$100-150k	-0.026	-0.030
	(0.027)	(0.027)
\$60-100k	0.008	0.003
	(0.025)	(0.025)
\$35-60k	-0.049*	-0.049*
	(0.027)	(0.026)
Controls: Age, Region		✓
Observations	3291	3291

Note: The table reports the results from equation (2) where Y_i is an indicator for whether household i is More Concerned about climate change. We classify a household as More Concerned if it is in either the concerned or alarmed Six Americas categories. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A8: Clean Equipment by Environmental Preferences

%	(1) Electric Veh.	(2) Hybrid (NPI)	(3) Solar Panels	(4) Heat Pumps	(5) Appl./Weath.
(a) Own/Lease					
More Concerned	10	19	21	28	81
Less Concerned	4	16	15	28	80
(b) Considered					
More Concerned	45	44	68	17	40
Less Concerned	20	21	55	14	27

Note: This table reports the fraction of households in the sample owns/leases or considered each type of equipment, split by their level of climate concern. In (1) and (2), we drop households who reported that they do not drive or do not need a car. In (3) the sample is restricted to households with single-family detached homes, excluding those who reported that solar panels are not feasible for their house/roof. Appendix Table A13 reports the share of households who have *installed* solar panels and heat pumps by level of climate concern.

Table A9: Environmental Preferences and Clean Equipment Decisions
Probit, Marginal Effects

	Own/Lease Equipment			Considered Equipment		
	(1) Electric Veh.	(2) Hybrid (NPI)	(3) Solar Panels	(4) Electric Veh.	(5) Hybrid (NPI)	(6) Solar Panels
More Concerned	0.044***	0.013	0.045*	0.245***	0.225***	0.137***
	(0.010)	(0.016)	(0.025)	(0.020)	(0.022)	(0.037)
Age, Income, Region	✓	✓	✓	✓	✓	✓
Observations	2154	2172	823	1996	1683	672

Note: This table reports probit marginal effects for equation (3). Table 4 reports results for the equivalent linear probability model. Robust standard errors are in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A10: Environmental Preferences and Clean Equipment Decisions
Weighted Linear Probability Model

	Own/Lease Equipment			Considered Equipment		
	(1)	(2)	(3)	(4)	(5)	(6)
	Electric Veh.	Hybrid (NPI)	Solar Panels	Electric Veh.	Hybrid (NPI)	Solar Panels
More Concerned	0.050***	0.018	0.035	0.228***	0.193***	0.168***
	(0.015)	(0.022)	(0.033)	(0.026)	(0.027)	(0.047)
Age, Income, Region	✓	✓	✓	✓	✓	✓
Observations	2154	2172	823	1996	1683	672

Note: This table reports a weighted linear probability model for equation (3). Weights are calibrated with iterative proportional fitting so that our sample precisely matches the CPS distributions of age, education, gender, income, race, region. Table 4 reports results for the unweighted linear probability model. Robust standard errors are in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A11: Environmental Preferences and Clean Equipment Decisions
Linear Probability Model

(a) Own/Lease

	(1) Electric Veh.	(2) Hybrid (NPI)	(3) Solar Panels	(4) Heat Pumps	(5) Appliances	(6) Weath./Insul.
Alarmed	0.074***	0.065**	0.069*	-0.025	0.016	0.027
	(0.017)	(0.026)	(0.039)	(0.025)	(0.030)	(0.038)
Concerned	0.035**	0.046*	0.090**	-0.041*	-0.021	-0.069*
	(0.016)	(0.026)	(0.040)	(0.025)	(0.031)	(0.037)
Cautious	0.013	0.071***	0.036	-0.032	-0.044	-0.067*
	(0.016)	(0.027)	(0.041)	(0.026)	(0.032)	(0.039)
Disengaged or Doubtful	0.008	0.042	0.039	-0.024	-0.018	-0.030
	(0.015)	(0.028)	(0.040)	(0.027)	(0.033)	(0.041)
Age, Income, Region	✓	✓	✓	✓	✓	✓
Observations	2152	2170	822	1979	1976	2056
Adjusted R^2	0.075	0.025	0.066	0.005	0.037	0.049

(b) Considered

	(1) Electric Veh.	(2) Hybrid (NPI)	(3) Solar Panels	(4) Heat Pumps	(5) Appl./Weath.
Alarmed	0.414***	0.375***	0.353***	0.045	0.348***
	(0.030)	(0.034)	(0.061)	(0.034)	(0.092)
Concerned	0.240***	0.245***	0.181***	0.020	0.216**
	(0.029)	(0.032)	(0.064)	(0.033)	(0.087)
Cautious	0.129***	0.130***	0.178**	0.006	0.136
	(0.029)	(0.033)	(0.069)	(0.034)	(0.090)
Disengaged or Doubtful	0.068**	0.082**	0.180***	0.009	0.173*
	(0.029)	(0.033)	(0.070)	(0.035)	(0.094)
Age, Income, Region	✓	✓	✓	✓	✓
Observations	1995	1682	672	1426	284
Adjusted R^2	0.148	0.102	0.059	0.017	0.070

Note: This table reports the coefficients for each level climate concern in a regression analogous to equation (3) where Y_i is an indicator for whether household i had purchased (panel a) or considered purchasing (panel b) a given type of equipment. The omitted category is Dismissive. Disengaged and Doubtful are pooled together due to the small sample sizes in those groups. Table 4 reports results for aggregated levels of climate concern. Robust standard errors are in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A12: Environmental Preferences and Clean Equipment Decisions
Probit, Marginal Effects

	Own/Lease Equipment			Considered Equipment		
	(1)	(2)	(3)	(4)	(5)	(6)
	Electric Veh.	Hybrid (NPI)	Solar Panels	Electric Veh.	Hybrid (NPI)	Solar Panels
Alarmed	0.069***	0.067**	0.067*	0.418***	0.372***	0.356***
	(0.018)	(0.027)	(0.038)	(0.030)	(0.034)	(0.060)
Concerned	0.036**	0.049*	0.091**	0.243***	0.242***	0.183***
	(0.017)	(0.027)	(0.040)	(0.029)	(0.032)	(0.064)
Cautious	0.014	0.072**	0.035	0.133***	0.127***	0.178***
	(0.017)	(0.028)	(0.040)	(0.029)	(0.033)	(0.069)
Disengaged or Doubtful	0.006	0.044	0.036	0.071**	0.080**	0.183***
	(0.018)	(0.029)	(0.041)	(0.029)	(0.033)	(0.069)
Age, Income, Region	✓	✓	✓	✓	✓	✓
Observations	2152	2170	822	1995	1682	672

Note: This table reports probit marginal effects for each level of climate concern in a regression analogous to equation (3) where Y_i is an indicator for whether household i had purchased (columns 1-3) or considered purchasing (columns 4-6) a given type of equipment. The omitted category is Dismissive. Disengaged and Doubtful are pooled together due to the small sample sizes in those groups. Table A9 reports results for aggregated levels of climate concern. Robust standard errors are in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A13: Equipment Installation by Environmental Preferences

	(1)	(2)
% Installed	Solar Panels	Heat Pumps
More Concerned	18	9
Less Concerned	12	10

Note: This table reports the share of households who have installed solar panels or heat pumps split by their level of climate concern. In (1) the sample is restricted to households with single-family detached homes, excluding those who reported that solar panels are not feasible for their house/roof. Table A8 reports the share of households who own/lease or have considered solar panels and heat pumps by level of climate concern.

Table A14: Equipment Installation by Environmental Preferences

	Linear Probability Model		Probit Marginal Effects	
	(1)	(2)	(3)	(4)
	Solar Panels	Heat Pumps	Solar Panels	Heat Pumps
More Concerned	0.052**	-0.011	0.052**	-0.010
	(0.024)	(0.013)	(0.024)	(0.013)
FE: Age, Income, Region	✓	✓	✓	✓
Observations	823	1980	823	1980

Note: The table reports the results from equation (3) where the outcome is having *installed* solar panels or heat pumps. Columns (1)-(2) are linear probability model coefficients, (3)-(4) are probit marginal effects. In (1) and (3) the sample is restricted to households with single-family detached homes, excluding those who reported that solar panels are not feasible for their house/roof. Table 4 reports results for owning/leasing solar panels (3) or heat pumps (4) or considering them (b). Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

A.5. Additional Analyses

We show that our two measures of environmental preferences are highly correlated. Specifically, we show that households that are more concerned about aggregate climate change are more likely to care about reducing their individual emissions. We estimate the following linear probability model:

$$Y_i = \alpha + \sum_{j=1} \beta_j \cdot (\text{Climate concern})_{ij} + \eta_i + \nu_i + \gamma_i + \varepsilon_i \tag{10}$$

where Y_i is an indicator for whether household i ranked reducing carbon emissions an important factor for their purchase of at least one type of clean equipment or residential solar. $(\text{Climate concern})_{ij}$ is an indicator variable that equals one if household i is in Six Americas' group j. Variables η_i, ν_i, and γ_i denote fixed effects for age, income, and census region, respectively. Table A15 reports the results.

There is a monotonic relationship between a household's level of climate concern and the likelihood that they ranked reducing carbon emissions as an important factor. For example, households with the highest level of climate concern are 51 percentage points more likely to have ranked reducing carbon emissions as an important factor than those with the lowest level of concern. We show the same pattern among those households who have considered but not yet purchased clean equipment in Table A18. Table A16 reports probit marginal effects for the same specification, and Table A17 shows the results with survey weights. Again, the results are unchanged. These strong positive correlations suggest that households with stronger environmental preferences not only care about reducing their own emissions, but also global emissions.

Table A15: Percent Ranking Carbon Emissions as Important

	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
Alarmed	0.242***	0.243***	0.514***	0.510***
	(0.020)	(0.020)	(0.024)	(0.025)
Concerned	0.072***	0.071***	0.311***	0.310***
	(0.013)	(0.014)	(0.023)	(0.024)
Cautious	0.032***	0.028**	0.139***	0.137***
	(0.012)	(0.012)	(0.022)	(0.022)
Disengaged or Doubtful	0.000	0.000	0.061***	0.062***
	(0.008)	(0.009)	(0.019)	(0.020)
Controls: Age, Region, Income		✓		✓
Observations	2018	2018	2018	2018

Note: The table reports the results from equation (10) where Y_i is an indicator for whether household i ranked reducing carbon emissions the most important (columns 1 and 2), or either first or second important (columns 3 and 4) factor in their decision to purchase at least one type of clean equipment. The omitted base group is Dismissive. Disengaged and Doubtful are pooled together due to the small sample sizes in those groups. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A16: Percent Ranking Carbon Emissions as Important
Probit, Marginal Effects

	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
Alarmed	0.242***	0.244***	0.514***	0.510***
	(0.020)	(0.020)	(0.024)	(0.024)
Concerned	0.072***	0.072***	0.311***	0.311***
	(0.013)	(0.013)	(0.023)	(0.023)
Cautious	0.032***	0.029***	0.139***	0.138***
	(0.012)	(0.011)	(0.022)	(0.022)
Disengaged or Doubtful	0.000	0.001	0.061***	0.062***
	(0.008)	(0.008)	(0.019)	(0.019)
Controls: Age, Region, Income		✓		✓
Observations	2018	2018	2018	2018

Note: The table reports probit marginal effects for a regression analogous to equation (10) where Y_i is an indicator for whether household i ranked reducing carbon emissions the most important (columns 1 and 2), or either first or second important (columns 3 and 4) factor in their decision to purchase at least one type of clean equipment. The omitted base group is Dismissive. Disengaged and Doubtful are pooled together due to the small sample sizes in those groups. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A17: Percent Ranking Carbon Emissions as Important
Weighted Linear Probability Model

	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
Alarmed	0.199***	0.198***	0.447***	0.451***
	(0.022)	(0.023)	(0.033)	(0.033)
Concerned	0.074***	0.070***	0.298***	0.305***
	(0.016)	(0.015)	(0.032)	(0.032)
Cautious	0.040**	0.033**	0.125***	0.130***
	(0.015)	(0.016)	(0.029)	(0.029)
Disengaged or Doubtful	-0.000	-0.004	0.045*	0.049*
	(0.007)	(0.009)	(0.026)	(0.025)
Controls: Age, Region, Income		✓		✓
Observations	2018	2018	2018	2018

Note: The table reports a weighted linear probability model for equation (10) where Y_i is an indicator for whether household i ranked reducing carbon emissions the most important (columns 1 and 2), or either first or second important (columns 3 and 4) factor in their decision to purchase at least one type of clean equipment. Weights are calibrated with iterative proportional fitting so that our sample precisely matches the CPS distributions of age, education, gender, income, race, region. The omitted base group is Dismissive. Disengaged and Doubtful are pooled together due to the small sample sizes in those groups. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

Table A18: Percent Ranking Carbon Emissions as Important
Considered Equipment

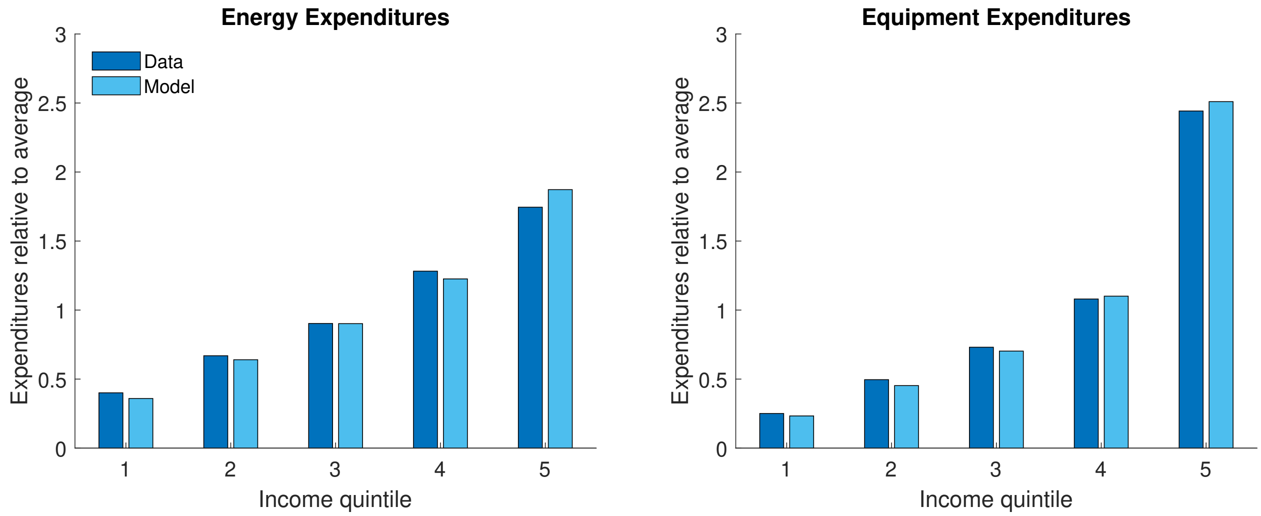
	Most Important		1st or 2nd	
	(1)	(2)	(3)	(4)
Alarmed	0.396***	0.401***	0.697***	0.700***
	(0.021)	(0.022)	(0.021)	(0.022)
Concerned	0.134***	0.136***	0.395***	0.395***
	(0.018)	(0.018)	(0.025)	(0.025)
Cautious	0.039***	0.040**	0.207***	0.203***
	(0.015)	(0.016)	(0.027)	(0.027)
Disengaged or Doubtful	0.018	0.017	0.119***	0.117***
	(0.013)	(0.014)	(0.025)	(0.026)
Controls: Age, Region, Income		✓		✓
Observations	1767	1767	1767	1767

Note: The table reports the results from equation (10) where Y_i is an indicator for whether household i ranked reducing carbon emissions the most important (columns 1 and 2), or either first or second important (columns 3 and 4) factor in their *consideration of* at least one type of clean equipment. Robust standard errors are reported in parentheses. Significance at the 0.1, 0.05, and 0.01 levels indicated by *, **, and ***, respectively.

B. Model Calibration

We divide households into ten equal sized income groups. The values of labor productivity in each group, $\{\zeta\}$, equal: $\{0.18, 0.3, 0.41, 0.52, 0.64, 0.79, 0.98, 1.25, 1.69, 3.22\}$.
The amount of solar a household can install for each value of labor productivity, $\{S(\zeta)\}$, equals: $\{0.05, 0.08, 0.1, 0.13, 0.15, 0.17, 0.2, 0.24, 0.28, 0.39\}$.

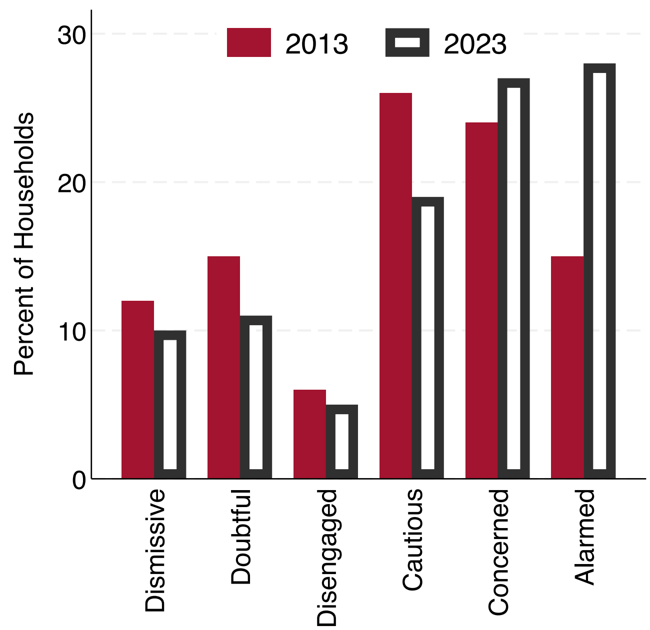
Figure B1: External Validation: Energy and Equipment Expenditures



Note: The left and right panels plot energy expenditures and equipment expenditures respectively by income quintile in the model (dark blue) and data (light blue). Quintile one corresponds to the lowest income group.

C. Quantitative Results

Figure C1: Historical Shift in Public Concern About Climate Change



Note: The figure plots the 2013 distribution of climate change concern from the CCAM project (red filled) and our baseline distribution (black boxes) from our survey data.