What matters for the racial disparity in clean heating technology adoption? Evidence from U.S. heat pumps

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Abstract

A growing body of literature has documented that minority groups have installed fewer clean energy technologies, but the varying extent of this adoption gap and its underlying causes remain less understood. This study utilizes household-level demographic and property data to explore the racial disparity in air source heat pump adoption in nine U.S. East Coast states. I quantify the heat pump adoption gap between White and minority households at the ZIP code level, and then use a machine learning approach to decompose the contributors to the racial disparity. The gap in building age is the most important contributor, followed by income gap, cooling degree days, and natural gas prices or access. The importance of building age persists even when conditioning on income, possibly due to historic or contemporary discrimination in housing markets. The study also provides causal evidence that an increase in heating and cooling demand and natural gas prices can widen the racial gap in heat pump adoption. Policies may not necessarily alleviate the gap though. Loan programs slightly reduce the gap, while small rebate programs widen the racial gap.

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1 Introduction

Addressing climate change necessitates a swift reduction in carbon emissions through clean energy transitions. These transitions encompass an increase in clean energy production, such as the promotion of wind and solar power generation and energy storage, and the adoption of clean energy technologies for end-use applications, including zero-emission vehicles and electric heat pumps. However, such a significant transition is likely to result in uneven impacts across various societal groups. The existing literature has highlighted that lower-income and Black, Indigenous, and people of color (BIPOC) communities, even after controlling for income, have demonstrably less access to clean energy technologies (Brown 2022; Edwards et al. 2023; Hsu and Fingerman 2021; Min et al. 2023; Sunter et al. 2019). A rapid and efficient shift towards widespread adoption of clean technologies could yield unequal outcomes, leaving certain groups behind. The specific reasons why minority groups have limited access and what could explain the racial inequality remain under-explored in current research, yet understanding these dynamics is crucial to addressing this inequality. This paper aims to contribute to this wider inquiry by focusing on the adoption of air source heat pumps in the U.S.

The heat pump is a highly energy-efficient technology used for space heating and cooling that operates solely on electricity. Numerous studies have indicated that electrifying space heating via heat pumps presents a feasible and cost-effective approach to significantly reduce carbon emissions in the buildings sector (Davis et al. 2018; Edenhofer 2015; MacKay 2008). In comparison to hydrogen-only space-heating technologies, the heat pump is projected to be 50% lower in cost (Baldino et al. 2021), and in many locations, it can lead to private energy bill savings and increased home prices (Shen et al. 2021; Vaishnav and Fatimah 2020). National, state-level, and city-level decarbonization plans increasingly incorporate heat pumps and have provided generous subsidies in recent years, such as the U.S. Inflation Reduction Act and Massachusetts Clean Energy and Climate Plan. The International Energy Agency (IEA) has recommended that the share of residential heat pumps globally must double by 2030 to get on track with the Net Zero Emissions by 2050 (IEA 2022).

Despite these efforts, the current penetration rate of heat pumps is still low (IEA 2022), and minority groups installed much fewer heat pumps disproportionately in the U.S. (Edwards et al. 2023). For instance, in North Carolina, one of the states with the highest number of heat pumps, 32% of White households have heat pumps, compared to 18% of Black households and 25% of Hispanic households in 2021[1]. This racial disparity in heat pump adoption is observed in many other states as well (see figure 1)[2]. Few studies have

[1] The calculation of the heat pump adoption rate relies on household-level DataAxle and CoreLogic data, as referenced in this paper. For specific data details, please refer to section 2.

[2] Similar to other clean energy technologies, the adoption of heat pumps among low-income households is also often relatively lower than higher-income groups, particularly in warmer regions where heat pumps are well-suited for use. Please refer to Figure B.1 in Appendix B for the distribution of heat pump adoption rates across nine U.S. East Coast states, categorized by income.

explored the underlying reasons for racial disparity in the adoption of heat pumps. With a comprehensive understanding of these unexplored mechanisms, targeted policies can be crafted and applied, ensuring a balance between efficiency and equity in promoting the adoption of clean energy technologies such as heat pumps.

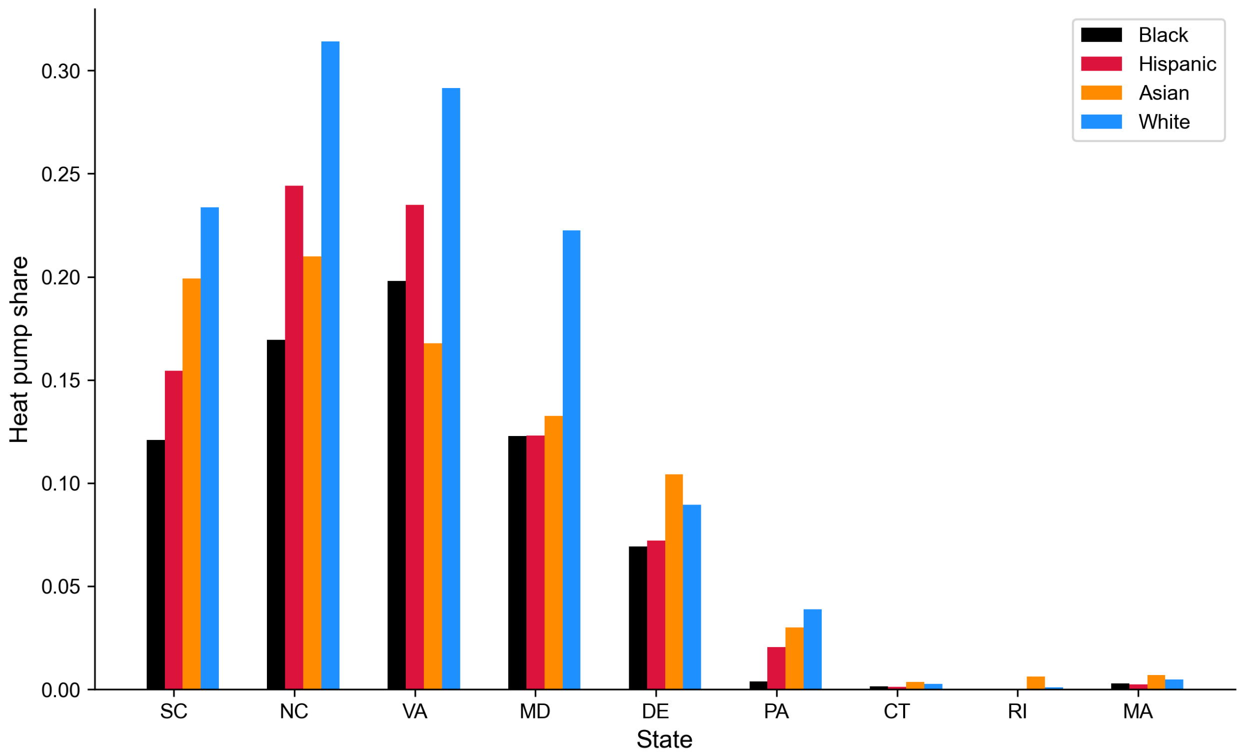

Figure 1: The heat pump adoption share by racial groups in nine U.S. states in 2021.

To investigate this question, this paper utilizes household-level demographics and property data sourced from DataAxle and CoreLogic to decompose the drivers of the racial disparity in air source heat pump adoption in nine U.S. East Coast states, namely South Carolina (SC), North Carolina (NC), Virginia (VA), Maryland (MD), Delaware (DE), Pennsylvania (PA), Connecticut (CT), Rhode Island (RI), and Massachusetts (MA). The selection of these nine states is based on a combination of factors including data availability, the distribution of minority residences, and the diversity of climates within the sample.

First, I create an standardized variable to measure the level of adoption inequality at the cross-sectional ZIP-code level in 2021 and employ a two-step data driven approach to decompose the drivers of the inequality. I use the Z-statistic score to measure the difference in heat pump adoption rates between majority households (White) and minority households (Hispanic and Black). Then, relying on a stylized model of energy-efficiency investments, I comprehensively review the factors related to heat pump adoption (such as income and wealth disparities, home ownership gap, education gap, market share, temperature, energy prices, incentives, building attributes, and others). Drawing on the cross-sectional variations in these factors and the heat pump adoption gap, this study decomposes the contributions of these factors. I first use LASSO regression to select the optimal specification for predicting the adoption gap with the least Mean Squared Error (MSE), then apply Shapley Value regression to decompose the contribution of each selected predictor to the R^2.

The results of the pooled cross-section regression indicate that building age gap, income gap, cooling degree days, natural gas price, and heat pump market share are the five most significant predictors, sorted by their R^2 contribution. The within-state-variation and within-county-variation regression analyses reveal that building age gap and income gap are the two most important predictors. In all three specifications, building age gap emerges as the single most crucial predictor, with the largest R^2 contribution, rather than income gap, wealth gap, homeownership gap, or education gap. Specifically, I discover that, even conditional on income, low-income Black and Hispanic families are more likely to own older properties than low-income White families. This discrepancy can be attributed to the historical discriminatory housing policies and practices in the U.S., which will be discussed in detail in section 7. The presence of limited electrical wiring, outdated building structures, and poor insulation in older buildings contributes to the higher upfront cost of heat pump installations and lower future fuel savings, presenting significant obstacles to heat pump adoption.

The cross-sectional decomposition analysis identifies temperature (cooling degree days) and energy price (natural gas price) as crucial secondary contributors to adoption disparities. Thus, I investigate causal evidence of temperature and energy price's impact on the adoption disparity in the second analysis. Using panel data of heat pump adoption from 2010 to 2021 at the household-year level and a linear probability model with two-way fixed effects, the impacts of annual average temperature and natural gas prices on the probability of new heat pump installation are estimated. The results indicate that White households are more responsive to the annual average temperature than Black and Hispanic households in warm regions (SC and NC). Specifically, my findings indicate that the gap in new heat pump adoption probability between White and Black households increased by 1.3 percentage points, and between White and Hispanic households increased by 0.6 percentage points, when the local annual average temperature decreased from 61 °F to 57 °F. In warm regions where heat pumps are currently suitable for use, a decrease in temperature can lead to higher heating demand and higher fuel savings for heat pumps, but it can also exacerbate inequalities in heat pump installations. In contrast, the study finds no significant temperature responsiveness in heat pump adoption in colder regions (the other seven states).

With respect to energy prices, the analysis is focused on the impact of natural gas price, rather than electricity price, given the complexity of electricity price effects[3]. According to the linear probability model, in states where natural gas and electricity are the primary heating fuels (such as SC, NC, VA, MD, DE), this study finds that a 1% increase in the

[3] An increase in electricity prices can increase heat pumps' fuel savings compared to electric resistance heating but decrease fuel savings compared to fossil fuel heating.

annual average natural gas price can result in a 0.018%, 0.011%, and 0.003% increase in the probability of new heat pump adoption among White, Hispanic, and Black households, respectively. Thus, an increase in the natural gas price can exacerbate the heat pump adoption gap across racial groups.

The estimated impacts of temperature and natural gas prices above are identified based on within-location annual variations and could be attributed to residents' psychological expectations of future fuel savings across different years (Busse et al. 2015; He et al. 2022; Loewenstein et al. 2003). It should be noted, however, that these impacts may be relatively small when compared to those resulting from long-term, constant changes, such as the geographic cross-section variations discussed in the above decomposition analysis. Nevertheless, the causal evidence derived from short-term annual variations provides significant support for the hypothesis presented in this paper. In summary, the empirical evidence highlights that the benefits of using heat pumps are higher when triggered by changes in temperature, or energy prices, leading to increased incentives for adoption. However, the increase in heat pump adoption can be differentiated across racial groups, exacerbating the existing racial inequality in adoption.

To promote the adoption of heat pumps, various incentives have been provided by the government and local electric utilities, with rebate and loan programs being the two most widely used incentives for heat pumps in the U.S. There is evidence of the positive impact of the incentives on heat pump adoption (Shen et al. 2022). However, few studies have investigated whether these incentives reduce or exacerbate adoption inequality. In the last part of analysis, I explore the role of loan and rebate programs on the racial disparities in heat pump adoption. Specifically, I estimate the causal impact of a loan incentive in MD on heat pump adoption by racial groups using a difference-in-differences approach in conjunction with matching and geographic discontinuity along the border between MD and VA. Loan programs can alleviate credit constraints for low-income and minority groups, which is a common reason for "energy efficiency gap"[4], but these groups may also experience an information gap and face higher application costs in accessing loan programs. The result of this study indicates that the loan program can increase the probability of households having heat pumps by 0.11% for the overall population within a period of two years, while the impact is more significant for Hispanic and Black populations, with an increase of 0.02% compared to White populations. The estimated effect is relatively small, as the average adoption rate in the sample is approximately 10%. This finding echoes the results of the decomposition analysis, which indicates that the loan incentives are not selected by the LASSO regression. Nonetheless, the findings suggest that the loan program can slightly reduce the racial gap in heat pump adoption.

Lastly, this study presents suggestive evidence on the relationship between rebate programs and racial inequality in heat pump adoption. Specifically, the study examines the 2010 State Energy-Efficient Appliance Rebate Program (SEEARP) and the Massachusetts

[4]The "energy efficiency gap" refers to the difference between the potential energy savings that could be achieved through energy efficiency measures and the actual energy efficiency realized in practice.

Clean Energy Center (MACEC) rebate program between 2014 and 2019. Rebate amounts range from $100 to $600 per ton (or 12,000 BTU/hr) in the programs studied. To investigate the potential racial disparities in these programs, I match rebate recipients' home addresses with household demographic data for the Massachusetts program and ZIP code level demographic data for the SEEARP program in SC, NC, VA, MD, and DE. The findings suggest that a disproportionately smaller share of Black and Hispanic families received the heat pump rebate compared to White families. This indicates a potential racial disparity in access to these rebate programs and underscores the need for further investigation to better understand the barriers to equitable participation.

This paper makes a significant contribution to the literature on access disparity in clean energy technologies. A growing body of research has demonstrated that lower-income and BIPOC households and renters face barriers to accessing clean energy technologies, such as rooftop solar panels, electric vehicles, energy-efficient appliances, and housing units (Barbose et al. 2020; Borenstein and Davis 2016; Brown 2022; Davis 2019; Gao and Zhou 2022; Hsu and Fingerman 2021; Min et al. 2023; Paulos 2017; Sunter et al. 2019). However, there are limited studies examining the access disparity in heat pumps, and few studies provide a comprehensive empirical investigation of the underlying drivers of the racial disparity. This paper addresses this research gap by conducting the first study to review and decompose the factors contributing to heat pump adoption inequality across different racial groups. Additionally, this paper provides the first empirical evidence linking temperature change and energy price to racial inequality in clean energy technology adoption. This research comes at a critical time when addressing climate change and transitioning away from fossil fuels have become increasingly imperative. Using causal evidence, this paper sheds light on the potential impact of these factors on exacerbating the existing racial inequality in heat pump adoption.

This paper also contributes to the literature on policy impacts on access to clean energy technologies across different groups. A growing body of research has shown that commonly used policies aimed at promoting the adoption of clean energy technology, such as subsidies, tax credits, and efficiency standards, can have negative impacts on lower-income groups and favor higher-income individuals (Bennear 2022; Borenstein and Davis 2016; Bento et al. 2009; Davis and Knittel 2019; Jacobsen 2013; Levinson 2019; Bruegge et al. 2019). However, other studies have found that programs specifically targeted at low-income groups can increase the adoption rate of clean energy technologies in that group. For instance, the Enhanced Fleet Modernization Program in California limits subsidy eligibility to households residing in disadvantaged communities or with incomes at or below 400% of the federal poverty line. Muehlegger and Rapson (2018) find that this program increased the adoption rate of electric vehicles in low-income groups. Moreover, O'Shaughnessy et al. (2020) report that solar leasing programs, property assessed clean energy (PACE) financing programs, and community-based campaigns significantly increased the adoption rate of solar panels in low-income households. In line with this literature, this study estimates the impacts of loan and rebate programs on heat pump adoption equity. The findings suggest that while the loan program can mildly reduce the racial adoption gap, the rebate program may potentially widen the gap. Moreover, this study contributes to the literature by shedding light on an additional barrier faced by minorities: the building age gap, which persists even after controlling for income, a factor that has often been overlooked in previous studies primarily focused on income disparities.

2 Data

Household property data. I retrieved household-level property data from *CoreLogic*, a well-known data provider in the real estate industry. This national panel dataset spans the years 2009 to 2021 and encompasses all the land parcels in the U.S., including both residential and commercial properties. In this study, I focus on all the units for residence, including single-family houses, residential and commercial apartments, condominiums, and duplexes. The dataset contains detailed building attributes for each property, such as its address, assessed value, building structure, building and land size, building material and style, year built, and heating and cooling equipment, among other features. The county or township assessors performed building assessments periodically to collect this information for property tax evaluation. Although these large-scale assessments were not conducted annually, property owners are required by law to apply for a permit before installing certain types of retrofits, such as a heat pump that involves electric work. Such retrofits trigger a property tax reassessment, although this does not necessarily result in a higher tax rate. Therefore, the CoreLogic data includes annual observations of heat pump adoption. Not all counties factor heat pumps into their property assessments. For instance, some counties in SC and NC, states with a high prevalence of heat pumps, have reported zero heat pumps in the CoreLogic dataset. To ensure the integrity of the sample, I have excluded counties that reported zero heat pumps in at least one period. I have also removed data for ZIP codes in years with abnormal heat pump counts, such as counts that are less than one-tenth of the average for that ZIP code across all years. It is worth noting that in this paper, I define heat pumps as air-source heat pumps, excluding water-source and geothermal heat pumps.

Household demographics data. The household-level demographics data used in this study was obtained from *DataAxle*. This national dataset is organized by households and includes a range of demographic information in 2021, such as the household address, income, wealth, purchasing power, age of the household head, number of children, and the likelihood of the household being either a homeowner or renter. Additionally, the ethnicity of each household member is also recorded. DataAxle compiled information from various sources, including new utility connections, real estate tax assessments, voter registrations, credit card billing statements, public records, telephone directories, and many others. The household income and wealth data are derived from the MRI survey, a widely recognized national consumer survey. They first matched DataAxle's consumer data to the MRI survey using name and address matching and then used a statistical model to adjust the data locally to align with census distributions. To ensure the reliability of the

DataAxle data, I use this data to calculate the ZIP-level median household income and the proportion of households belonging to different ethnic groups. I find that these measures are highly and positively correlated with the ZIP-level estimates derived from the U.S. 2021 American Community Survey (ACS) data (see detailed Pearson's correlation coefficients for these comparisons in Table A.1).

Matching property data with demographics data. In order to match the CoreLogic property data with the DataAxle demographic data at the household level, a two-step process was employed. Firstly, a perfect match was made by comparing the full street addresses of each dataset. For the remaining unmatched households, a nearest-neighbor matching technique was applied, which involved identifying the three closest DataAxle neighbors for each CoreLogic household based on geographic coordinates. The average distance in the nearest-neighbor matching was 100 meters and the maximum distance was 2 kilometers in the sample. Numeric demographic information, such as income and wealth, were calculated as the average of the three closest neighbors, whereas categorical fields such as ethnic groups were measured as the most frequent occurrence. In total, 74% of matches were achieved through a perfect street address match, whereas 26% were made using the nearest-neighbor approach in my analysis. Finally, I got a sample consisting of a total of 13,622,001 households across nine states.

Other supporting data. The annual heating and cooling degree day data at the weather station level were obtained from the U.S. National Oceanic and Atmospheric Administration website. To transform the weather data to ZIP-code level, an average of heating and cooling degree days across all stations was calculated for each ZIP code and year, weighted by the inverse distance between the ZIP code and each station. Annual residential sales and revenues of electric utilities were acquired from the U.S. Energy Information Administration's (EIA) 861 forms. The annual natural gas prices at the state level were sourced from the EIA website. To account for inflation, all energy prices were adjusted by the Consumer Price Index (CPI) and converted to 2021 U.S. dollars. In addition, nationwide electric and natural gas utility service territory shape files were obtained from the Homeland Infrastructure Foundation-Level Data (HIFLD) platform, which is maintained by the U.S. Department of Homeland Security. These shape files were then used to match each utility's service territory to ZIP codes and determine whether a ZIP code had access to utility gas service. The study also examined incentive policies for residential heat pumps implemented between 2009 and 2021 in the nine states. To do so, the Database of State Incentives for Renewables & Efficiency (DSIRE) and various sources, including state and federal government websites and local utilities, were reviewed. County-level data on residents' opinions about climate change, such as the percentage of adults who believe in global warming, were obtained from the Yale Program on Climate Change Communication website (Howe et al. 2015). Lastly, education levels of individuals from different ethnic groups were extracted from *L2 data*, a reputable voter data provider.

3 A framework to understand heat pump adoption and its adoption disparity

Following the literature on energy efficiency investments (Allcott and Greenstone 2012; Berkouwer and Dean 2022; Shen et al. 2022), this study establishes a stylized model of heat pump adoption to investigate the factors that influence the adoption of heat pumps, as well as the potential racial disparities associated with it. Energy-efficient heat pumps are often more costly than conventional Heating, Ventilation, and Air Conditioning (HVAC) systems, but offer fuel cost savings and environmental benefits in the future. When deciding between a heat pump and a classical HVAC system, a rational and time-consistent agent would opt for the heat pump if and only if the upfront additional adoption cost is smaller than the net present value of future fuel savings, combined with the "warm glow" utility (Andreoni 1990) derived from contributing to environmental benefits:

$$\underbrace{u(P_h - P_c)}_{\text{initial costs}} < \underbrace{\sum_{t=1}^{T}[\delta^t \cdot u(\sigma_{ct} - \sigma_{ht})]}_{\text{fuel savings}} \quad + \quad \underbrace{u(\tau_h)}_{\text{warm glow}} \tag{1}$$

where $u(.)$ represents the utility function, P_h and P_c represent the initial installation costs of a heat pump and a classical HVAC system[5], respectively, and T represents the lifetime of the heating system. The future fuel cost savings of using a heat pump compared to a classical HVAC system are denoted by $\sigma_{ct} - \sigma_{ht}$, while the "warm glow" utility of using a heat pump is denoted by $u(\tau_h)$. The discount rate is represented by δ. Notably, the installation cost may exceed the equipment price, as additional building retrofitting work (such as laying ventilation ducts) may be required. When P_h results in an agent being indifferent between adopting the heat pump and the classical HVAC system, it becomes the agent's maximum willingness to pay (WTP) for choosing the heat pump. Assuming a linear utility function, the WTP is expressed as follows:

$$WTP = P_c + \sum_{t=1}^{T} \delta^t \sigma_t + \tau_h \tag{2}$$

In a population where individuals have different levels of WTP and initial installation costs, those individuals whose WTP exceeds the initial installation cost will choose to install the heat pump. According to the data presented in Figure 1, the majority population has installed a significantly higher number of heat pumps compared to the minority population. This inequality can be explained as follows:

[5] In a scenario where a consumer, who initially did not consider heat pumps in their choice set and already has a new classical HVAC system installed at home, becomes aware of the heat pump option and evaluates whether to switch to it, the initial installation cost P_c is regarded as zero in this model.

$$\frac{1}{N^w}\sum_{i=1}^{N^w}\mathbb{1}\{WTP_i^w > P_{h,i}^w\} > \frac{1}{N^m}\sum_{i=1}^{N^m}\mathbb{1}\{WTP_i^m > P_{h,i}^m\} \tag{3}$$

Here, the subscript i represents individuals, while the superscripts w and m indicate the White and minority populations, respectively. In summary, the racial disparities in heat pump adoption can be attributed to the varying initial installation costs, fuel savings, "warm glow" effects, and discount rates for future benefits across different racial groups. The following sections provide a more detailed discussion of these factors.

Initial installation costs. The installation of a heat pump involves more than just purchasing the equipment. Additional costs are incurred, such as remodeling ventilation ducts and upgrading electric wires, which vary among different households and buildings. For example, older homes with outdated infrastructure such as ducts and iron radiators are typically incompatible with air-source heat pumps, as these systems require high-temperature heating that can overshadow heat losses during transmission. Moreover, some older homes have limited electric wiring that cannot support the additional electricity usage of heat pumps. Therefore, these homes may require duct remodeling and electric wire upgrades for heat pump installation. Other building features, including size, type, and available space, also impact installation costs, with larger buildings requiring more capacity and potentially higher costs, single-family houses being easier to install extra space for heat pumps, and multifamily units benefiting from shared central heat pumps. Furthermore, subsidy incentives, such as rebates and low-interest loans, can reduce heat pump installation costs (Shen et al. 2022). These subsidies vary by region, period, and population, thus affecting the overall cost of installation. In a more comprehensive context, potential information search costs (e.g., identifying suitable contractors) (Gillingham et al. 2016; Shen et al. 2021) and cognitive costs (e.g., understand and think of the option of heat pumps) (Brent and Ward 2018; Houde 2018) may also contribute to the additional costs incurred.

Fuel savings. The efficiency of heat pumps is contingent upon the prevailing climate conditions. In colder climates, heat pumps tend to consume more electricity for heating compared to milder climates, thereby affecting the potential fuel savings (Vaishnav and Fatimah 2020). Additionally, the relative prices among various heating energy sources are essential to the fuel savings offered by heat pumps (Davis 2023). In the U.S., electricity, natural gas, and fuel oil constitute the three primary fuels for heating, with regional variations in the prevalence of each energy source. Building insulation also significantly influences heat pump fuel savings (Haralambopoulos and Paparsenos 1998; Junghans 2015), as heat pump efficiency is sensitive to insulation levels. Junghans (2015) demonstrates that heat pumps are less cost-effective compared to furnaces in buildings with poor insulation. The well-established principal-agent problem, associated with the "energy efficiency gap" (Davis 2011; Gillingham et al. 2012) , is also relevant to heat pump fuel savings. If renters bear the energy bills while homeowners retain the authority to install new heat pumps, there would be no change in the energy bills for the homeowners. In this scenario, the incentive for homeowners to adopt heat pumps would be greatly diminished as any future fuel savings would not accrue to them.

"Warm glow" effects. Existing literature suggests that the "warm glow" effect is associated with the characteristics of the buyers and the levels of contribution to environmental benefits (Ma and Burton 2016). The environmental benefits derived from heat pump usage are contingent upon the type of electricity grid to which they are connected. In space cooling applications, energy-efficient heat pumps are recognized for their potential to reduce electricity consumption and subsequent power generation emissions compared to traditional air conditioning systems. However, the situation regarding space heating is more nuanced due to the availability of multiple heating options for residents, including natural gas furnaces, fuel oil furnaces, and electric resistance heating systems. Emissions associated with electricity generation and the use of natural gas and oil furnaces exhibit regional variability (Holland et al. 2016). As a result, the environmental benefits of heat pumps are strongly influenced by regional factors (Vaishnav and Fatimah 2020). However, due to the complex nature of the calculations involved, it might be difficult for consumers to be fully aware of the environmental benefits.

Discount rates for future benefits. The valuation of future benefits plays a crucial role in individual energy efficiency investments (Allcott and Wozny 2014; Hausman 1979). Studies indicate that discount rates vary significantly among individuals (Samwick 1998), and that income level is reversely associated with an individual's discount rate (Hausman 1979). Specifically, low-income individuals often exhibit higher implicit discount rates due to their heightened financial insecurity and immediate needs for basic necessities, such as food. Moreover, limited access to credit and savings (Berkouwer and Dean 2022; Golove and Eto 1996) may further complicate low-income individuals' ability to invest in long-term projects.

The adoption of heat pumps is determined by the combined influence of the aforementioned factors, and it is possible that systematic differences in these factors across racial groups contribute to potential racial disparities in heat pump adoption rates.

4 Decomposing the drivers of racial inequality

In this section, I employ the cross-sectional geographical variation in the heat pump adoption gap and variations in other factors related to heat pump adoption among different racial groups in 2021 to empirically investigate what matters for the heat pump adoption gap.

4.1 Measuring heat pump adoption racial inequality

Before investigating the factors contributing to racial disparities in heat pump adoption empirically, it is necessary to establish a standardized measurement of such inequalities. Social inequality refers to the uneven distribution of resources, opportunities, and rewards among individuals or groups in a society, leading to social and economic disadvantages for certain groups (Boudon 1974). Heat pumps offer significant private and environmental benefits in almost half of the U.S. (Vaishnav and Fatimah 2020), with more regions set to benefit in the near future as the power grid becomes cleaner and cold-climate heat pumps become more efficient. In an ideal state of equality, the rate of heat pump adoption should be irrelevant to the race of the individuals involved, whether one conditions on factors like income, wealth, education, or other social endowments, or not. In other words, the adoption rate should be equal across all racial groups. Any deviation from this would constitute adoption inequality. One simple way to measure this is to calculate the difference in adoption rates between different racial groups. However, if one wants to compare adoption inequality across different regions, this measure could be problematic since the overall heat pump adoption rate varies significantly across regions. For instance, in areas with low heat pump adoption rates, the adoption rates of different racial groups tend to be low as well, and the difference between them tends to be smaller, which is irrelevant to the issue of inequality. Figure 2 (plot (a)) illustrates the heat pump adoption rates at the ZIP code level in our sample, which range from 0 to 1. In states with warm climates such as SC, NC, and VA, the adoption rate is relatively high, at around 0.2 to 0.5, whereas the adoption rate is very low, at approximately 0.003, in cold states such as CT, RI, and MA.

To measure the heat pump adoption gap in a standardized way, I borrow the idea from the Z statistic test commonly used to test the difference between two binomial distributions (Armitage et al. 2008). The Z-score value is calculated as the difference between the two sample proportions divided by the standard error of the difference. Once the Z-score is calculated, we can use a standard normal distribution to determine the probability of observing a Z-score as large as the calculated Z-score and to determine the probability that the two samples are significantly different. I calculate the Z-score of the heat pump adoption gap as follows:

$$Z\text{-score} = \frac{p_w - p_m}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_w} + \frac{1}{n_m}\right)}} \tag{4}$$

where $\hat{p} = \frac{n_w p_w + n_m p_m}{n_w + n_m}$; p_w and p_m are the heat pump adoption rates of White families and minority families, respectively; n_w and n_m are the number of White families and minority families, respectively. A positive and higher Z score indicates the probability that White families are more likely to install heat pumps than minority families is higher, and vice versa. For ZIP codes with zero heat pump adoption rate, I replace the Z score of heat pump gap with zero. The minority families in this analysis refers to Hispanic and Black families, as these are the two largest racial minority groups in the U.S.

I calculate the Z-score of the heat pump adoption gap at the ZIP code level to present the geographic heterogeneity of inequality in the nine states of my sample. The selection of these nine states is a result of various factors such as data quality, sample representativeness, and racial geographic distribution. Climate has a significant impact on the efficiency of heat pumps, and local heat pump penetration rates are highly correlated with climate. Therefore, I specifically chose nine states across different latitudes with varying climates to enhance the representativeness of my study. Additionally, minority populations, such as Black populations, are more likely to reside in coastal states, which further influenced the state selection. However, I am unable to include the states of New York and New Jersey in my sample, as the CoreLogic data did not count heat pumps in these two states. Despite this limitation, I believe that my sample provides a representative and diverse perspective on the issue of heat pump adoption inequality across different regions.

Figure 2 (plot (b)) displays a map illustrating the geographic variation of the heat pump adoption gap in 2021. Although White households install more heat pumps on average across the states (as shown in figure 1), the local heat pump adoption gap is mixed, with White households not being more likely to install heat pumps than minority households in every location. Another intriguing finding is that as the heat pump adoption rate increases in southern, warmer states, the heat pump adoption gap between White and minority households also significantly increases.

Table 1 presents the summary statistics for the Z-score of the heat pump gap at the ZIP code level, comprising a total of 2,356 ZIP code areas in the sample. Among the ZIP codes analyzed, 51% exhibit a higher installation rate of heat pumps by White households compared to minority households, and the differences are statistically significant in 17% of ZIP codes. In contrast, minority households installed more heat pumps in 30% of the ZIP codes, with a statistically significant difference observed in 10% of them. It is important to highlight that these comparisons are confined to ZIP codes for the purpose of conducting the decomposition analysis. It is essential to recognize that racial disparities at the statewide or nationwide level may diverge from these findings.

4.2 Covariates

Based on the framework established in section 3, I construct the following variables related to heat pump adoption. While it is not feasible to identify and measure all relevant factors, the variables constructed below cover the major aspects and have significant policy implications.

Variables associated with initial costs. The installation cost of a heat pump varies

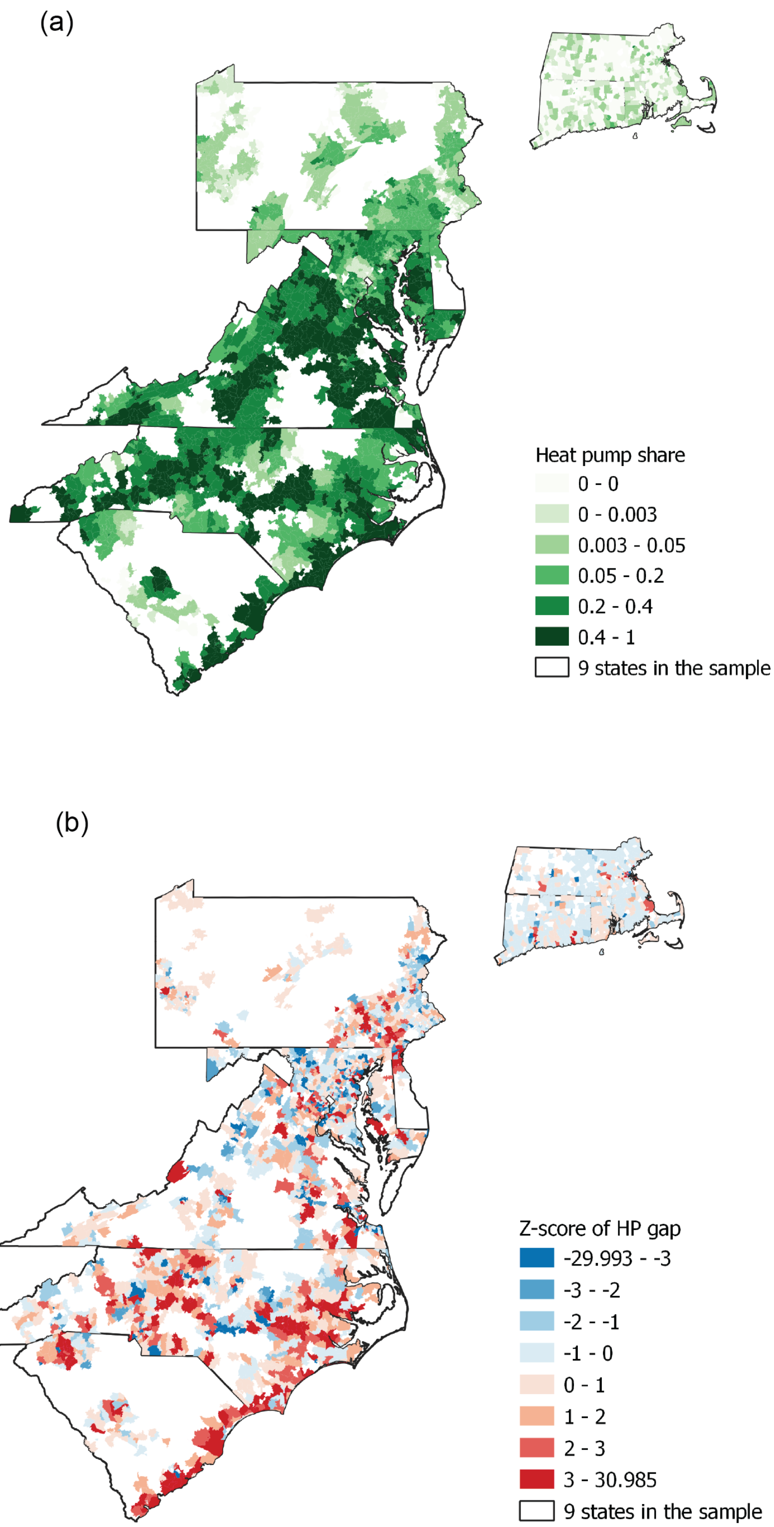

Figure 2: The heat pump adoption rate and racial gap at ZIP level in nine U.S. states in 2021 (Data unavailable in blank areas). Plot (a) shows the share of households with heat pumps and plot (b) shows Z-value of adoption rate between White families and minority families (Hispanic and Black). Positive Z-value means White families adopt more heat pumps.

based on building attributes, and as such, a uniform price cannot be established. In this study, three dimensions are utilized to measure building attributes: year built, total living area (in square feet), and housing type (single-family or multi-family). At the ZIP code level, the overall average and the T statistic score between White and minority populations are used to measure the level and gap of these three building attributes. The T-score is calculated using the following equation: $T = (M_w - M_m)/\sqrt{(s_w^2/n_w) + (s_m^2/n_m)}$, where M_w and M_m represent the means for White and minority households, respectively; s_w^2 and s_m^2 denote the respective variances; and n_w and n_m indicate the sample sizes for each group. Incentives, such as rebate and loan programs, can reduce the initial cost of installing a heat pump. For rebates, the following equation is used to measure the amount of rebates in the past ten years (2011-2021): $rebate_z = \sum_{t=1}^{10} r_{t,z}$, where $r_{t,z}$ represents the rebate amount for heat pumps in year t in ZIP code z. For loans, the following equation is used to measure loan incentives for the past decade: $loan_z = \sum_{t=1}^{10} l_{t,z}$, where $l_{t,z}$ is a dummy indicator taking the value of one if ZIP code z had a loan program for heat pumps in year t. Information searching costs and cognitive costs are difficult to measure directly but are highly correlated with individuals' education levels. Therefore, the overall ratio of individuals earning a bachelor's degree or higher, and the Z score of this ratio between White and minority individuals at the ZIP code level, is used to measure the education level and gap. It is important to note that the different equipment prices and installation labor costs across regions are not included in this study and represent a limitation of this paper. Future research is required to address these factors. Nevertheless, I included county fixed effects in one of my specifications, which effectively controls for the heat pump equipment price and labor installation cost. This is because these costs are expected to be uniform within a county and may not vary significantly.

Variables associated with fuel savings. To measure local climates, the average of annual heating and cooling degree days for the past decade (2011-2021) is used at the ZIP code level. The annual residential electricity prices at the utility level are approximated using the ratio of utility annual residential revenues to residential sales. The annual residential natural gas prices are included at the state level but in cases where ZIP codes lack access to utility natural gas, the natural gas price (or service cost) is set to an extreme high value (e.g., 9999). The overall electricity and natural gas service costs are then calculated by taking the average for the past decade. Building insulation is an important factor for fuel savings, but it is challenging to measure at the individual level. Instead, building age is utilized as a proxy for insulation quality (Haralambopoulos and Paparsenos 1998). Moreover, the overall average and the T score of the likelihood of property ownership between White and minority households are used to measure homeownership levels and gaps at the ZIP code level.

Variables associated with "warm glow". It is unlikely that general residents would accurately assess the environmental benefits of using heat pumps. As such, I assume that there is only a buy-in "warm glow" effect irrespective of contribution level to the environmental good (Ma and Burton 2016). The "warm glow" effect varies between individuals, and directly measuring this effect can be challenging. To approximate this, environmental opinion (e.g., the percentage of adults who believe in climate change) at the county level and education level and gap at the ZIP code level are used instead.

Variables associated with discounting. I use the overall average and the T score of income and wealth between White and minority households to measure income and wealth levels and gaps at the ZIP code level. Loan programs can relieve residents' credit and liquidity constraints and therefore influence implicit discount rates for private benefits, which has been incorporated into the analysis outlined previously.

Table 1 presents the summary statistics for the constructed variables outlined above.

Table 1: Summary statistics for cross-sectional decomposition analysis

Variable	Unit	Mean	Std. Dev.	Min.	Max.	N
Z score of heat pump gap		0.438	2.99	-29.993	30.985	2356
heat pump market share		0.172	0.214	0	0.943	2362
Inferred electricity price	$ per kWh	0.145	0.037	0.093	0.321	2358
Natrual gas service cost	$ per mcf	2491.494	4313.353	12.01	9999	2362
HTDD		4544.552	1098.117	1535.89	6877.405	2357
CLDD		1174.8	376.089	439.683	2581.482	2357
T score of income gap		5.498	9.122	-61.651	80.180	2353
Average income	$K	97.605	58.249	7.687	404.369	2362
T score of wealth gap		9.244	10.85	-31.054	94.447	2353
Average wealth	$K	1934.76	591.902	437.629	3900.396	2362
T score of ownership gap		4.017	5.659	-76.131	39.332	2353
Average owner status		8.226	0.731	1.333	8.926	2362
Z score of SF housing gap		0.747	4.767	-25.886	49.284	2340
Single-family housing ratio		0.921	0.129	0	1	2362
Climate opinion	%	72.493	6.006	50.98	85.837	2357
Z score of edu gap		4.9	4.337	-4.307	28.493	2349
Percentage above bachelor	%	0.284	0.111	0	1	2356
T score of year built gap		0.462	6.066	-99.595	73.406	2354
Average year built		1967.908	18.773	1896.989	2012.21	2362
T score of living area gap		1.111	3.269	-9.221	34.021	2353
Average living area	sq feet	2001.731	555.092	919.628	10366.497	2362
Rebate	$/ton*yrs.	1235.888	1600.215	0	4775	2362
Loan	yrs.	5.943	4.525	0	10	2362

Note: Unit of observation is the ZIP code level. In areas without access to utility gas, the natural gas service cost is set as 9999. The electricity price is approximated using the ratio of utility annual residential revenues to residential sales. Climate opinions are measured as the percentage of adults who believe in climate change (Howe et al. 2015). The owner status, pulled from DataAxle data, is represented by a score ranging from 0 to 9 and indicates the likelihood that the household owns their home.

4.3 Model selection and decomposition

Initially, I include all the predictors in an ordinary least squares (OLS) regression to assess their correlation with the heat pump adoption gap. Columns (1) and (4) in table 2 present the estimates, both with and without state fixed effects.

Then I employ a two-step data-driven approach to decompose the drivers of heat pump adoption gap. In the first step, I employ the Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani 1996) to select the most important predictors for heat pump adoption gap. By introducing a shrinkage penalty on the $L1$ norm of variable coefficients in an OLS regression, LASSO can shrink coefficients towards zero and ultimately eliminate them from the model. Specifically, the LASSO regression model is estimated as:

$$\hat{\beta}_{lasso} = \text{argmin}_{\beta} \left\{ \sum_{i=1}^{n} (z_i - \beta_0 \sum_{j=1}^{p} \beta_j x_{ij})^2 + \alpha \sum_{j=1}^{p} |\beta_j| \right\} \tag{5}$$

where z_i is the Z-score of heat pump adoption gap in ZIP code i, x_{ij} is the value of j_{th} explaining variable constructed in ZIP code i, β are the coefficients of variables, and α is the shrinkage penalty. The variables that remain after LASSO regression tend to have the strongest associations with the outcome variable. Before running the LASSO regressions, I standardized all the independent variables. Figure 3 shows the penalization path of coefficients as a function of penalty α. As α increases, fewer but more important predictors are retained. Then I selected the best specification by choosing the one with minimum 10th-fold cross-validated Mean Absolute Error (MAE). The pooled cross-sectional LASSO regression shows that building age gap, income gap, cooling degree days, natural gas service cost, and heat pump market share are the five retained predictors (in descending order of importance) in the best specification (see figure 3 plot(a)). For the within-state-variation regression, I regressed the Z-score of gap on state fixed effects and used the residuals for the LASSO regression. The optimal specification shows that building age gap and income gap are the only two predictors retained (see figure 3 plot(b)). Columns (2) and (5) in table 2 show the estimated coefficients of these selected predictors.

To further identify how much these predictors explain the heat pump adoption gap, I decompose the R^2 of the model selected by LASSO (Milosh et al. 2021). The Shapley Value regression is used to decompose the R^2 of the selected model (Lindeman 1980). In Shapley Value regression, the contribution of each predictor variable is estimated by comparing the model's fitted R^2 with and without that variable included. Specifically, the method involves calculating the difference in R^2 between all possible subsets of predictors, and averaging these differences to determine the contribution. The Shapley value of each predictor i is estimated as follows:

$$\varphi_i(\nu) = \frac{1}{|N|} \sum_{S \subseteq N \setminus \{i\}} \binom{|N|-1}{|S|}^{-1} (\nu(S \cup \{i\}) - \nu(S)) \tag{6}$$

where ν is a function that maps subsets of predictors to the resulting R^2, N is the set of predictors, and S are all possible subsets of N excluding i. Columns (3) and (6) in table 2 present the estimated percentages of R^2 contribution of each selected predictor. For the pooled cross-sectional specification, the R^2 contributions of building age gap, income gap, cooling degree days, natural gas service cost, and heat pump market share are 43%, 35%, 8%, 8%, and 6%, respectively. In the within-state-variation specification, the R^2 contributions of building age gap and income gap are 57% and 43%, respectively.

I performed a robustness check by incorporating county fixed effects to address the potential variability in heat pump equipment prices and labor installation costs. The results remain consistent, with the LASSO selecting building age gap and income gap in the optimal specification (see figure B.2 in appendix B). The R^2 contribution of these predictors are 53% and 47%, respectively.

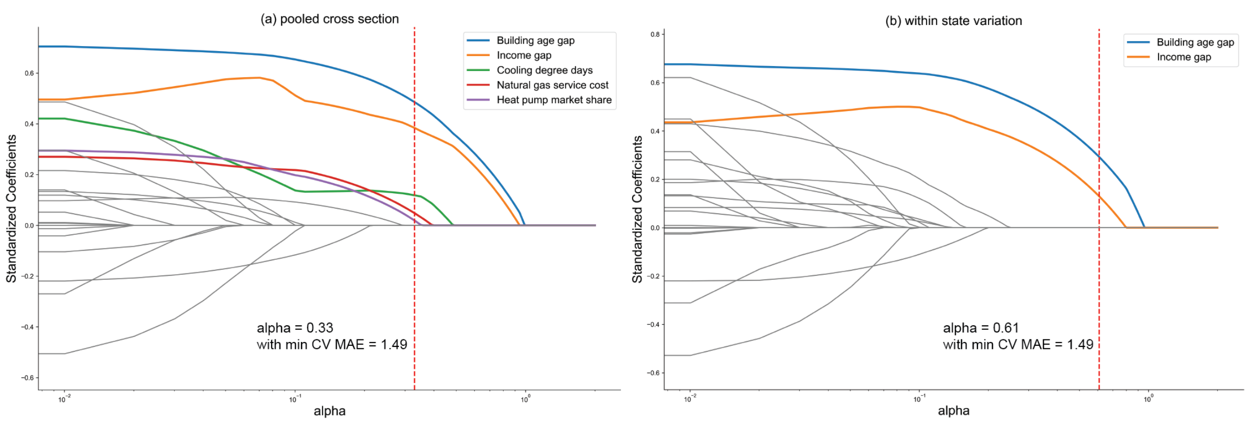

Figure 3: Lasso coefficients as function of alpha.

4.4 Findings and significance

The study findings demonstrate that the building age gap is the most significant predictor, followed by the income gap, in explaining the heat pump racial adoption gap, as evidenced by both pooled cross-sectional and within-state variation specifications. Specifically, the average building ages for White, Hispanic, and Black households in the 2021 sample are 52, 61, and 64 years, respectively, while the average incomes for these groups are \$102K, \$73K, and \$59K, respectively. As noted in Section 3, older buildings typically have outdated ventilation systems, limited electrical wiring, and poor insulation, resulting in higher initial installation costs and lower operating fuel savings. Furthermore,

Table 2: Decomposition analysis for heat pump adoption gap

	Pooled cross section			Within state variation		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Lasso	R^2 share	All	Lasso	R^2 share
Year built gap	0.7592***	0.7772***	0.43	0.7339***	0.6328***	0.57
	(0.1363)	(0.1377)		(0.1332)	(0.1429)	
Mean year built	0.0737			0.0782		
	(0.1081)			(0.1069)		
living area gap	0.0831			0.0854		
	(0.1119)			(0.1108)		
Mean living area	-0.0856			-0.0883		
	(0.1024)			(0.1029)		
Single-family housing gap	-0.2210*			-0.2261*		
	(0.1315)			(0.1307)		
Single-family housing ratio	0.3092*			0.2815		
	(0.1754)			(0.1770)		
Income gap	0.4804*	0.5765***	0.35	0.4689*	0.6855***	0.43
	(0.2535)	(0.1227)		(0.2560)	(0.1286)	
Mean income	-0.2163			-0.0978		
	(0.1808)			(0.1821)		
Wealth gap	0.6086			0.6541*		
	(0.3713)			(0.3808)		
Mean wealth	0.3483			0.3891		
	(0.2623)			(0.2640)		
CLDD	0.7127***	0.1883**	0.08	0.3246		
	(0.2495)	(0.0738)		(0.3076)		
HTDD	0.3117			-0.2881		
	(0.2384)			(0.4856)		
Natural gas price	0.2802***	0.2868***	0.08	0.2559***		
	(0.0638)	(0.0555)		(0.0655)		
Electricity price	0.2205**			-0.0516		
	(0.0880)			(0.1472)		
Heat pump market share	0.2926***	0.2834***	0.06	0.4145***		
	(0.0943)	(0.0711)		(0.1032)		
Ownership gap	-0.0427			-0.0617		
	(0.2447)			(0.2443)		
Mean owner status	-0.5867**			-0.5556**		
	(0.2283)			(0.2308)		
Climate opinion	-0.1358*			-0.0734		
	(0.0717)			(0.0713)		
Education gap	-0.5834***			-0.5743***		
	(0.1756)			(0.1769)		
Education level	0.3479**			0.1720		
	(0.1727)			(0.1793)		
Rebate	0.1444***			0.1027		
	(0.0544)			(0.0850)		
Loan	0.1052			0.2041		
	(0.0850)			(0.1461)		
Constant	0.4423***	0.4341***		1.0855**	0.4379***	
	(0.0554)	(0.0559)		(0.4465)	(0.0572)	
State FE	No	No		Yes	Yes	
R-squared	0.2141	0.1804		0.2246	0.1396	
Number of observations	2,336	2,351		2,336	2,353	

Note: *** p<0.01, ** p<0.05, * p<0.1. The outcome refers to the Z-score of the heat pump adoption gap. Explaining variables are standardized.

some old buildings may be subject to additional regulations that restrict exterior modifications. Income is a well-established factor in household energy efficiency improvements (Berkouwer and Dean 2022; O'Shaughnessy et al. 2020), as lower-income households may encounter more liquidity or credit constraints when attempting to finance energy efficiency investments. Figure B.1 demonstrates that heat pump adoption is less prevalent among lower-income households, particularly in warm states like SC, NC, VA, MD, and DE. Consequently, the building age and income disparities between the majority and minority populations are the primary drivers of the heat pump adoption gap.

More importantly, this study's findings reveal that the building age gap is a more critical predictor than the income gap. To systematically investigate the relationship between building age, income, wealth, and race, I compare the average building age between different racial populations by ten income quantiles and wealth quantiles[6] (see figure 4). Results show that higher-income and higher-wealth groups are more likely to own and reside in newer buildings. However, controlling for income and wealth, I find that low-income and low-wealth Black and Hispanic populations are more likely to own older buildings compared to low-income and low-wealth White populations. This pattern is consistently observed across all nine states (see figures B.3 and B.4). The building age gap net of income could be due to historical discriminatory housing market and policies (Christensen and Timmins 2018; Swope et al. 2022). More targeted policy interventions to address this housing racial gap are needed, as discussed further in Section 7.

Next crucial predictors for the heat pump adoption gap are cooling degree days and natural gas prices, which are associated with expected fuel savings. The results indicate that regions with higher natural gas prices and more cooling degree days tend to have a larger positive adoption gap, with White households installing more heat pumps than minority households. In warmer climates, heat pumps are more efficient for heating and generate more fuel savings for cooling, which may encourage more people to install them. However, the larger racial adoption gap in warmer climates could be due to the fact that White populations, with higher average incomes and newer buildings, may have more resources and fewer barriers to leverage the technology of heat pumps. Similarly, higher natural gas prices or a lack of access to utility gas may make electric heat pumps more appealing, but the higher initial cost, poorer building insulation, and higher discounting rates may impede minority groups from adopting them. I provide causal evidence on the impact of temperature and energy prices on heat pump racial adoption inequality in Sections 5.1 and 5.2.

Related to the above finding, the heat pump market share is another crucial predictor for the heat pump adoption gap. Regions with a higher market share tend to have a larger positive adoption gap. This may be due to the same reasons as above (favorable climate, energy prices, and other factors), as well as peer effects within communities (Bollinger and Gillingham 2012). This finding has significant policy implications, as governments

[6] The income and wealth quantiles are calculated based on the population, and I draw comparisons between different racial groups within the same income/wealth interval.

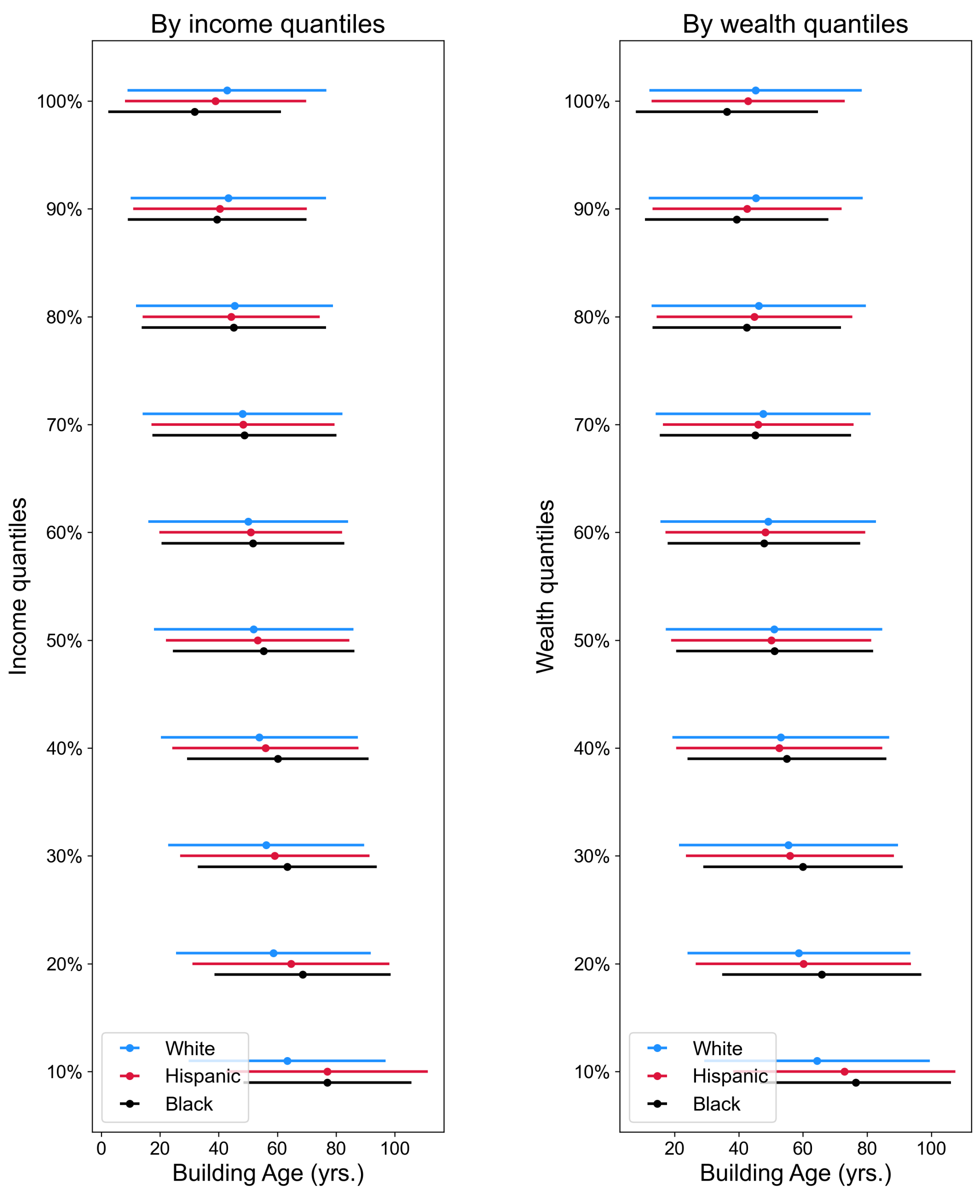

Figure 4: The average and standard deviation of building age by race in 2021. Note: left is by income quantiles and right is by wealth quantiles.

worldwide have set ambitious goals for rapidly deploying heat pumps in the near future. Whether the mass adoption of heat pumps will be an equitable and just transition is an important question that requires further exploration.

It is important to note that rebate and loan programs are well-established and widely implemented incentives for promoting residential heat pump adoption. According to this decomposition analysis, these policies do not appear to have played a significant role in determining the heat pump adoption inequality in my sample, as they were not selected by the LASSO regression. Despite this, there is a significant positive correlation between the rebate program and the heat pump adoption gap (shown in column (1) in table 2), which echoes prior literature indicating that certain incentives may exacerbate the inequality in clean energy technology adoption (Borenstein and Davis 2016; Bruegge et al. 2019; Levinson 2019). The correlation between loan programs and heat pump adoption gap is less clear from the decomposition analysis. In Section 6.1, I provide causal evidence regarding the impacts of the loan program on heat pump adoption racial inequality. Additionally, in Section 6.2, I present descriptive evidence on the impact of the rebate program on the racial equity.

Lastly, several studies have highlighted the substantial ownership gap between White and minority populations (Boehm and Schlottmann 2004; Collins and Margo 2011). In this study, I find that the average property ownership status is positively correlated with the heat pump market share, and the property ownership gap is positively correlated with the heat pump adoption gap using the ZIP code level sample. However, when including other covariates, the coefficient of ownership gap is not significant, as noted in columns (1) and (4) in Table 2. Additionally, the ownership gap is not selected by the LASSO model, which suggests that ownership may not be a crucial predictor for the heat pump racial adoption gap. In the sample of nine states used in this study, 15% of owned homes and 8% of rented homes had heat pumps installed in 2021. Landlords may opt to install heat pumps in their rental properties to attract tenants and enhance the value of their property (Fuerst and McAllister 2011; Shen et al. 2021).

4.5 Robustness check

In the baseline analysis outlined above, I employ Z-scores and T-scores to quantify the normalized difference (or gap) in heat pump adoption rates and associated sociodemographic characteristics. For robustness, I use an alternate method—the simple difference—to measure this gap in variables and subsequently re-conduct the decomposition analysis. Figure B.5 illustrates the path of the coefficients as I utilize Lasso for variable selection. The gap in building age consistently emerges as the most significant predictor, regardless of whether state fixed effects or county fixed effects are taken into account. In addition, the price of natural gas and cooling degree days are selected in both pooled cross-section and within-county-variation specifications, although the income gap is not selected across any of the three specifications. The results of this robustness check align with the main findings, but using the baseline approach is preferred for reasons discussed in section 4.1.

5 Temperature, energy prices, and racial inequality

5.1 Impact of temperature change on racial inequality

The cross-sectional decomposition analysis reveals that climate, measured by cooling degree days, is a significant predictor with a highly positive correlation with the racial gap in heat pump adoption. While it is challenging to estimate the causal impact of cross-sectional climate, the short-term temporal variations in annual weather patterns can aid us in illuminating the impact of temperature on the adoption gap of heat pumps, providing causal evidence.

Changes in heating or cooling demand resulting from temperature variations lead to fluctuations in the total fuel savings achieved by heat pumps, consequently influencing the incentives for households to adopt them. In other words, the maximum WTP for heat pumps varies as per the model presented in Section 3. However, the marginal change in WTP may differ among various racial groups, attributable to varying rates of discounting future fuel savings and differing home ownership statuses. Specifically, minority groups often exhibit lower average incomes, steeper discount rates, and a higher propensity towards home renting, thereby reducing the net present value of fuel savings for them and their WTP. Moreover, heat pump adoption rates are determined by the probability of WTP being higher than the initial installation cost. As discussed earlier, on average initial installation costs for minority groups are likely to be higher than those for the majority group, further reducing the responsiveness of the minority group to temperature changes and, hence, heat pump adoption. Thus, temperature variations, through increases in heating or cooling demand, may exacerbate the existing inequality in heat pump adoption.

To test this hypothesis, I construct a panel data at the individual household level, covering the years from 2010 to 2021. Table 3 presents the summary statistics for the panel data. Subsequently, a linear probability model with two-way fixed effects is employed to estimate the influence of yearly weather patterns on heat pump adoption.

$$\Delta Y_{ijst} = g(\boldsymbol{T}_{it}, R_j, C_s) + \boldsymbol{Elec}_{it} + \alpha_{st} + \delta_i + \epsilon_{ijst} \tag{7}$$

where Y_{ijst} is a binary variable to indicate the heat pump adoption status of household i with racial identity j (among White, Hispanic, and Black) in state s at year t. The first difference of Y_{ijst} is used as the outcome variable, where ΔY_{ijst} takes a value of one if household i adopted the heat pump at year t. The temperature response function, represented by $g(.)$, comprises of three elements. Firstly, $\boldsymbol{T}_{it}$ denotes the fourth-order polynomials of annual average temperature (°F) for household i at year t. The response function is also dependent on Rj, the racial identity, and C_s, the climate regions. I divide the sample of nine states into three climate regions, with SC and NC categorized as the warm region, VA, MD, DE as the temperate region, and PA, CT, RI, MA as the cold region. Additionally, the state-by-year fixed effects, denoted by α_{st}, are included to control for time-varying trends in each state that are not related to variations in yearly weather patterns. Particularly, individual household fixed effects, denoted by δ_i, are incorporated in the model to isolate the random within-location year-to-year variations in weather patterns and help us to identify the impact of temperature change on heat pump adoption (following Carleton et al. (2022)'s approach). To address the issue of time series autocorrelation, standard errors are clustered at the household level. ϵ_{ijst} is the error term.

Table 3: Summary statistics for panel regression analyses

Variable	Unit	Mean	Std. Dev.	Min.	Max.	N
First diff. in heat pump existence		0.003	0.059	0	1	89,940,888
Annual average temperature	°F	55.374	4.270	45.76	67.79	109,907,804
Annual heating degree days (HDD)		4697.342	1179.489	1309	7687	109,907,804
Annual cooling degree days (CDD)		1212.434	428.9599	342	2681	109,907,804
HDD + CDD		5909.776	814.5094	3729	8151	109,907,804
Inferred electricity price	$ per kWh	0.152	0.031	0.092	0.392	109,889,064
Natural gas price	$ per mcf	2183.287	4117.723	11.239	9999	109,937,313

Note: The unit of observation for regressions is at the household-year level. The sample includes White, Hispanic, and Black households located in South Carolina, North Carolina, Virginia, Maryland, Delaware, Pennsylvania, Connecticut, Rhode Island, and Massachusetts from 2010 to 2021.The temperature, heating degree days, and cooling degree days data are at the ZIP code level, while the electricity price is at the utility level and the natural gas price is at the state level. These data have been matched to the households. For households without access to utility gas, the natural gas price is set to an extreme value of 9999.

Although the within-location annual temperature change can be considered random and exogenous, it could still be correlated with heating and cooling fuel prices, such as electricity, natural gas, and fuel oil, which also have an influence on heat pump adoption. While the primary focus of this section is on the impact of heating and cooling demand rather than energy prices, I control for the effect of fuel prices. The model includes fourth-order polynomials of utility-level annual electricity price $\boldsymbol{Elec}_{it}$. As I only have access to state-year level data on natural gas and fuel oil prices, and the regression already includes state-by-year fixed effects, I have chosen not to include the variables of natural gas and fuel oil prices in the regression.

In this specification, I assume that once a household installs a heat pump, they will consistently utilize it for their heating needs and they will not face the question again to decide whether installing a heat pump or not in following years. Thus, I exclude the observations after a household installed the heat pump. In this analysis, I do not use a Probit or Logit model because these non-linear models rarely converge when involving a large number of fixed effects (Busse et al. 2015; Liao 2020) due to the incidental parameters problem (Greene 2004). The fixed effects are important to the identification in my specification. Instead, the generalized least squares (GLS) method is employed as a compromise to estimate the model. Since the outcome variable is a binary variable, the coefficients of the independent variables are directly interpretable as the marginal impact on the probability of adopting a new heat pump. The estimated impacts could be attributed to people's expectations for future fuel savings following the adoption of the heat pump. People may utilize the temperature of the year as a basis for inferring future energy consumption for heating and cooling purposes (Busse et al. 2015; He et al. 2022; Loewenstein et al. 2003).

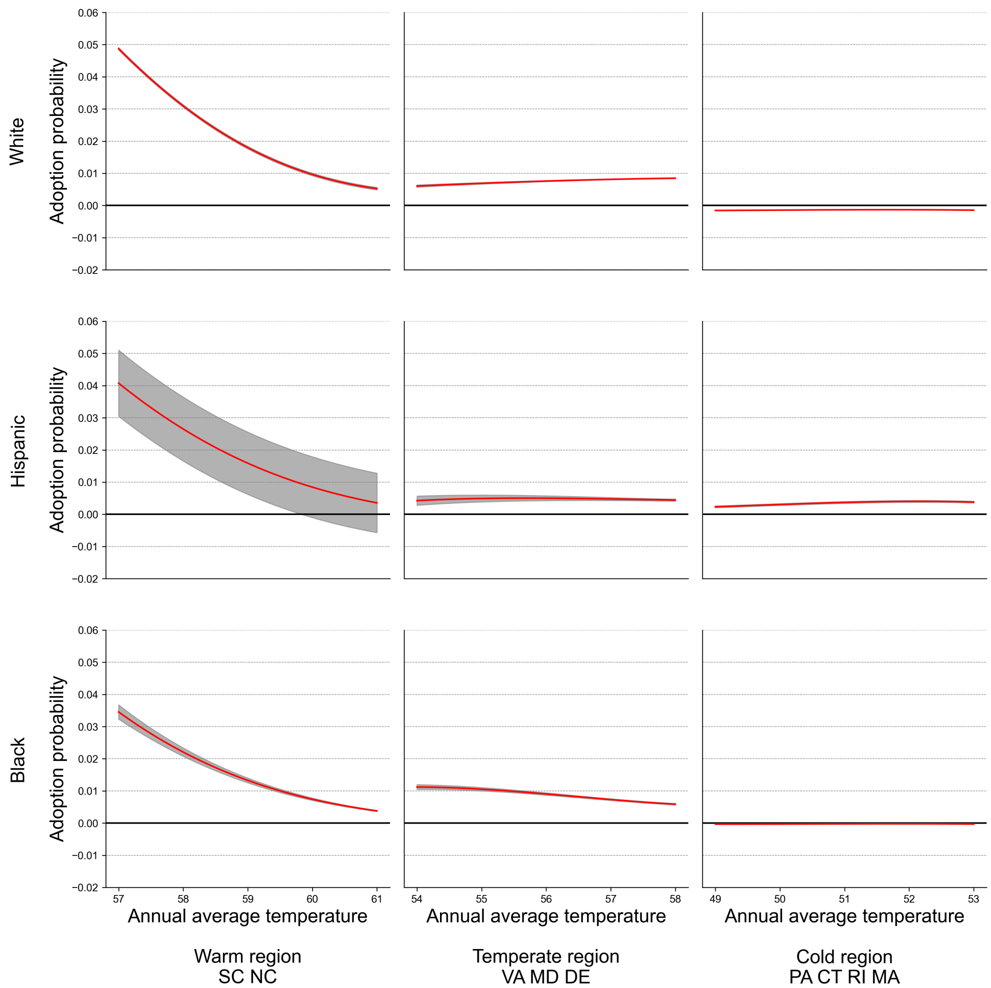

Figure 5: The impact of annual average temperature (°F) on the adoption probability of heat pumps by race and region. Note: Gray shaded areas are 95% confidence intervals.

Figure 5 illustrates the relationship between temperature and the probability of adopting new heat pumps among households. Specifically, the plot shows the predicted response functions at the average value of electricity price, using the estimated coefficients from equation 7. The response functions are presented for nine subsamples, which are disaggregated based on three racial groups and three climate regions. The results reveal that only households in the warm climate region (comprising SC and NC in my sample) demonstrated a significant response to temperature changes. Specifically, a decrease in temperature was associated with a significant increase in the probability of installing a heat pump, likely due to the rise in heating demand. Conversely, there was no significant increase in heat pump adoption in response to an increase in temperature. This indicates that the impact of temperature change on heat pump adoption in the warm region is mainly driven by heating demand rather than cooling demand. This finding could be attributed to the fact that conventional air conditioning units can typically handle hot weather, but struggle to provide sufficient heating during cold winters[7]. Given that many households in this warm region rely on electricity for heating, they are more inclined to adopt energy-efficient heat pumps during a colder winter.

There was an insignificant temperature response in the temperate and cold climate regions. In the current power grid, the private benefits of heat pumps, such as fuel savings, are ambiguous and close to neutral in the temperate region, while in the cold region, they are negative (Vaishnav and Fatimah 2020). Consequently, residents' WTP for adopting a heat pump is lower, and their response to temperature change is also insignificant.

More importantly, I observe that the slope of the temperature response function is steeper for White households as compared to Hispanic and Black households. Figure 6 plots the gap in the predicted adoption probability across different temperatures between White and Hispanic households, as well as between White and Black households. Specifically, the gap in heat pump adoption probability widens with a decrease in temperature and a corresponding increase in heating demand. The White-Black and White-Hispanic gap in adoption probability increased by 1.3 and 0.6 percentage points, respectively, when the annual average temperature is 57 F$^\circ$compared to 61 F$^\circ$. This empirical result supports the hypothesis outlined above.

As a robustness check, I also estimate the function of heat pump adoption in response to changes in both heating and cooling demand. To do so, I replace $\boldsymbol{T}_{it}$ with the fourth-order polynomials of the sum of annual heating degree days and cooling degree days in equation 7. This approach accounts for the fact that heat pumps can be used for both heating and cooling purposes. The results, shown in Figure B.6 in Appendix B by racial groups and regions, are consistent with the earlier findings. Specifically, only residents in the warm climate region demonstrated a significant response to the changing heating and cooling demand, and White households exhibited a stronger response compared to Hispanic and Black households.

Additionally, I carry out a further robustness check by reestimating the functions using a sample consisting solely of homeowners, which eliminates the potential influence of

[7]Conventional air conditioning units often possess a heating function, typically facilitated by either electric resistance heating or a reversed refrigeration cycle. However, their efficiency is generally lower compared to that of heat pumps. Consequently, these conventional units may not perform well in extremely cold weather conditions.

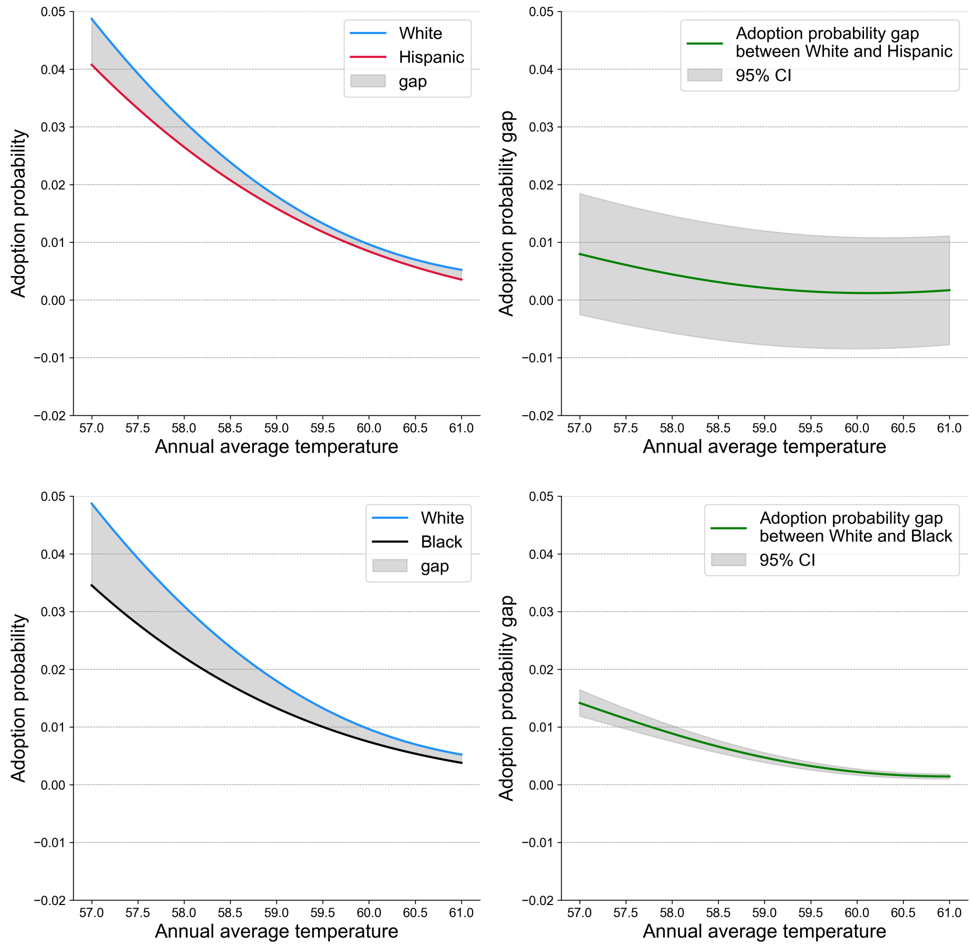

Figure 6: The association between temperature change and heat pump adoption probability gap in NC and SC.

split incentives. The data from DataAxle includes a home ownership score ranging from 1 to 9, signifying the likelihood of owning a home. A score of 9 implies a 100% likelihood that the household owns their home. I limit the sample to households with an ownership status score of 9. The outcomes from this estimation align closely with the results from the primary analysis (see figures B.7 and B.8).

5.2 Impact of energy prices on racial inequality

The cross-sectional decomposition analysis reveals the significant role of utility natural gas prices in determining the racial gap in heat pump adoption. By examining annual variations in these prices, we can estimate their impact on adoption by different racial groups. Similar to the impact of temperature changes, energy price fluctuations influence the fuel savings associated with heat pumps and can incentivize adoption. However, the response to these changes may vary across racial groups, potentially exacerbating inequalities in adoption.

Electricity prices can influence fuel savings, but the relationship between the two is more complex than that of natural gas prices. This is because electricity can be used not only for heat pumps, but also for electric resistance heating, which is less energy efficient than heat pumps. Consequently, when electricity prices increase, holding natural gas prices constant, the fuel savings of heat pumps relative to natural gas furnaces are lower, but relative to electric resistance heating, they are higher. To avoid ambiguity, the impact of electricity prices on the racial gap in heat pump adoption is not estimated, and the focus is instead on natural gas prices.

To test the impact of natural gas prices, a panel dataset is constructed including households located within natural gas utility service territories in SC, NC, VA, MD, and DE covering the years 2010-2021. Figure B.9 in appendix B shows the trends in residential natural gas prices in the five states, demonstrating significant variations. Households located in PA, CT, RI, and MA are excluded from the analysis due to their low heat pump penetration rates in these cold states, where residents' response to changes in natural gas prices could be minimal. Then, I fit a linear probability model as follows:

$$\begin{aligned} &\Delta Y_{ijst} = \beta \log(Ng_{st}) + \boldsymbol{Elec}_{it} + \boldsymbol{HDD}_{it} + \boldsymbol{CDD}_{it} + \alpha_t + \delta_i + \epsilon_{ijst} \\ &\text{with } j = \{\text{White, Hispanic, Black}\} \end{aligned} \tag{8}$$

The binary variable Y_{ijst} indicates the heat pump adoption status of household i with racial identity j in state s during year t. The natural gas price in state s and year t is denoted as Ng_{st}, while $\boldsymbol{Elec}_{it}$ represents the fourth-order polynomials of the annual electricity price at the utility level. The variables $\boldsymbol{HDD}_{it}$ and $\boldsymbol{CDD}_{it}$ represent fourth-order polynomials of annual heating and cooling degree days, respectively. Fixed effects for year (α_t) and household (δ_i) are included. Standard errors are clustered at the household level. Controlling for electricity prices is necessary, as natural gas is a major source of power generation and is correlated with electricity prices, while electricity prices can also influence heat pump adoption. Heating and cooling degree days are also controlled for, as natural gas prices may be correlated with heating demand, which are in turn related to heat pump adoption. One common challenge in identifying consumers' demand response to natural gas prices is the mutually causal relationship between consumption and price. However, in the case of heat pump adoption, the adoption of a heat pump is unlikely to influence natural gas prices, since few households install heat pumps each year, and it would not significantly impact the overall power loading or natural gas demand. Year fixed effects help control for trends in income growth, which may be correlated with heat pump adoption. Under the assumption that no other time-variant confounders are influencing heat pump adoption, the estimate of the impact of natural gas prices on heat pump adoption is causal. Also, it is worth noting that the estimated impact could be explained by residents' future expectation of fuel savings based on the present natural gas price each year.

The coefficient β can be interpreted as the percentage change in the probability of new heat pump adoption resulting from a one percent increase in natural gas prices. The difference in coefficients between different racial groups (e.g., $\beta_{white} - \beta_{hispanic}$, $\beta_{white} - \beta_{black}$) can be interpreted as the change in the heat pump adoption gap resulting from a one percent increase in natural gas prices.

Table 4 presents estimates of the impact of natural gas prices on heat pump adoption by the three racial groups. A one percent increase in natural gas prices can result in a 0.018%, 0.011%, and 0.003% increase (with statistical significance) in the probability of new heat pump adoption for White, Hispanic, and Black households, respectively. Specifically, the response is significantly larger for White households than for Hispanic and Black households. This empirical result supports the hypothesis that increasing natural gas prices leads to a larger racial gap in heat pump adoption.

As a robustness check, I re-estimated the regressions using a sample that includes only homeowners, and the results remain consistent (see Table A.2).

Table 4: Impact of natural gas price change on heat pump adoption by race

	(1) All	(2) White	(3) Hispanic	(4) Black
log(natural gas price)	0.015***	0.018***	0.011***	0.003***
	(0.0003)	(0.0003)	(0.0009)	(0.0008)
4th polynomials of elec price	Yes	Yes	Yes	Yes
4th polynomials of HDD	Yes	Yes	Yes	Yes
4th polynomials of CDD	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
R-squared	0.0087	0.0096	0.0049	0.005
Number of observations	41,296,249	33,046,818	2,714,485	5,534,946
Number of households	5,148,441	4,157,366	328,996	662,079

Note: *** p<0.01, ** p<0.05, * p<0.1. The outcome is a dummy indicates new heat pump adoption for each year. The model includes households located in natural gas utility service territories in South Carolina, North Carolina, Virginia, Maryland, and Delaware. Column (1) includes households from the three racial groups.

6 Public policy and racial inequality

6.1 Impact of loan program on racial inequality

Incentive policies such as rebate and loan programs were not found to play a crucial role in explaining the racial inequality of heat pump adoption in my cross-section decomposition analysis using the LASSO model. Nevertheless, incentive policies have been considered as important levers to promote the adoption of heat pumps and they have cost a considerable amount of public funding. Prior studies have estimated the impact of rebate and loan programs on heat pump adoption (Shen et al. 2022) and the impacts of various incentives on income equity in rooftop solar adoption (O'Shaughnessy et al. 2020). However, few studies have examined policy effects on promoting equity in heat pump adoption across different racial groups. Currently, rebate and loan programs represent the two most commonly utilized incentives for promoting heat pump adoption in the U.S. This section employs a triple-differences estimator in conjunction with matching and geographic discontinuity techniques to estimate the disparity in the impacts of a loan program on heat pump adoption across different racial groups. In the subsequent section 6.2, I will delve into the equity implications of the rebate program on heat pump adoption, with detailed descriptive evidence.

In February 2011, the Maryland Department of Housing and Community Development initiated the Be SMART financing program to support energy upgrades in residential, affordable multifamily, and small commercial buildings (Lambert and Carter 2014). The program offers loans with a low interest rate of 6.99% and up to $30,000 in financing for energy efficiency measures such as air source heat pumps. Eligibility for the Be SMART program is contingent on a credit score of 640 or higher for Maryland homeowners. To estimate the impacts of the loan program on different racial groups, this study focuses on a buffer area along the MD-VA border between 2009 and 2013. During this period, the VA side of the buffer area did not offer any loan programs for air source heat pumps, providing a control group. The sample does not include periods after 2013, as some ZIP code areas in the buffer zone have missing heat pump counts beyond that year.

It is essential to consider the potential influence of other incentives for air source heat pumps that may operate concurrently with the Be SMART program. To address this concern, I comprehensively reviewed the DSIRE database and the websites of utilities and governments. The review revealed that the only incentive for air source heat pumps during the study period was the State Energy-Efficient Appliance Rebate Program (SEEARP), a federal government initiative that provided different rebate regimes for energy-efficient appliances in each state. In 2010, MD residents were eligible for a $500 rebate for purchasing air source heat pumps, while VA residents received a rebate of $300 (Hoffmeyer 2015). The difference in the rebate amount is not expected to significantly affect heat pump adoption, as the average purchase price of air source heat pumps in 2010 was $7,040 in both states (Hoffmeyer 2015). Moreover, residents received the rebate solely within the year

2010, prior to the launch of the Be SMART program, which further reduces the possibility of confounding effects. The SEEARP program is unlikely to bias the loan effect estimate, if we have a plausible pre-treatment parallel trend in the DID setting.

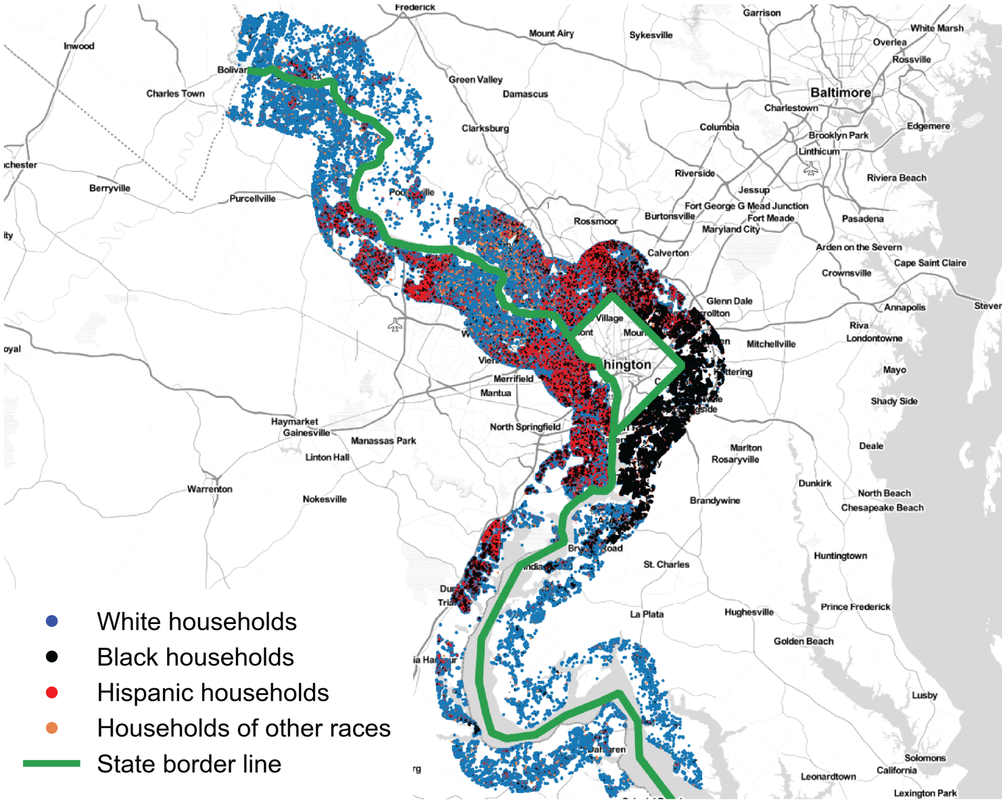

Figure 7: The sample of households for estimating loan effects in the buffer area (5 miles each side) along the border between Maryland and Virginia.

This analysis focuses specifically on a buffer area along the state border that spans a width of 10 miles (5 miles on each side), as illustrated in figure 7. This sampling strategy provides a geographically high-resolution analysis that ensures both the treated and control groups are located within the DMV (DC-MD-VA) metropolitan area[8] and share similar economic conditions, including the heating equipment and installer market. However, there are still differences in household-level attributes across the border such as income, wealth, and building features, which can also influence residents' decision on adopting a heat pump at different periods (see descriptive statistics of households in table 5). Conditioning on the observed covariates helps obtain parallel trend between the two groups (Roth et al. 2023). Following Heckman et al. (1997), Heckman et al. (1998) and Fowlie et al. (2012), to avoid the assumptions about the relationship between the outcome and covariates and to maintain the overlap of covariates distribution between treated and control units, I employ a semi-parametric conditioning strategy and use the following generalized DID matching estimator to estimate the loan's effect on heat pump adoption:

[8]The District of Columbia (DC) has been excluded from the sample.

$$\hat{\beta}_{DID} = \frac{1}{N_1} \sum_{j \in \mathcal{I}_1} \left\{ \left(Y_{j,\mathrm{t}^1}(1) - Y_{j,\mathrm{t}^0}(0)\right) - \sum_{k \in \mathcal{I}_0} w_{jk} \left(Y_{k,\mathrm{t}^1}(0) - Y_{k,\mathrm{t}^0}(0)\right) \right\} \tag{9}$$

where $\mathcal{I}_1$ and $\mathcal{I}_0$ denote the sets of households in the treated and control groups, respectively. t^1 and t^0 refer to the periods after and before the launch of the loan program, respectively. The outcome variable of interest Y is the probability of heat pump adoption. The weight placed on household k, which constructs the counterfactual estimate of household j, is represented by w_{jk}. In empirical practice of this analysis, I apply a K-Nearest-Neighbors propensity-score matching technique. Specifically, for each treated household across the three racial categories (White, Hispanic, Black) in MD, the five most similar control households in VA are matched based on their household-level covariates, including household income, wealth, purchasing power, home ownership, children count, house head age, building type (e.g., single-family housing and multi-family housing), and building year built. After matching, each household is assigned with a weight.

This analysis is limited to a sample comprising three racial groups, namely White, Black, and Hispanic populations. Descriptive statistics pertaining to households in both the treated and control groups, before and after the matching process, are showcased in Table 5. Additionally, Table 5 provides a breakdown of descriptive statistics for each of the three racial categories within the treated group, alongside their corresponding matched control groups. The matching procedure results in smaller differences in observed covariates between the treated and control groups, although statistical significance is still observed in most cases, possibly due to the larger sample size. However, it is worth noting that the parallel trend assumption does not require a perfectly balanced sample.

The three racial groups within the treated group in MD show significant demographic differences, consistent with the state averages. Notably, post-matching White households in the treated group display an average income of \$203K, whereas the equivalent figures for Black and Hispanic households are considerably lower at \$100K and \$120K respectively. Moreover, post-matching White households in the treated group are more prone to reside in single-family homes, possess home ownership, have a larger number of children, and have older heads of households compared to Black and Hispanic households.

To assess the validity of the parallel trend assumption, I conduct an event study for the entire sample and for each of the three racial groups in the treated group. The analysis involves regressing the dummy outcome of heat pump adoption at the household level on the interaction terms between the treated group indicator and a vector of year dummies. The regression controls for residential electricity prices, natural gas prices, year fixed effects, and household fixed effects, while observations are weighted by the weights generated by the matching and standard errors are clustered at the household level. Figure 8 displays the results of the event study. Without matching, significant differential trends are observed in the pre-treatment period, although treatment effects are much larger during periods post-treatment. After matching, no significant differential

Table 5: Demographic attributes of households for DID estimation on the loan effect

	Before Matching			**After Matching**		
	Treated group	Control group	Diff.	Treated group	Control group	Diff.
(a) Three races:						
N of households	220,213	205,844		167,845	199,314	
Household income	145.66	182.59	-36.93***	163.8	172.54	-8.74***
Household wealth	2279.63	2548.8	-269.17***	2456.76	2517.84	-61.08***
Purchasing power	111.84	140.22	-28.38***	125.59	132.62	-7.03***
Single-family housing	0.9	0.76	0.14***	0.89	0.97	-0.08***
Home owner status	8.3	7.97	0.33***	8.3	8.38	-0.08***
Children count	0.51	0.46	0.05***	0.51	0.54	-0.03***
Household head age	55.47	52.42	3.05***	55.32	54.39	0.93***
Building year built	1966.03	1980.88	-14.85***	1968.19	1968.64	-0.45***
(b) White households:						
N of households	107,660			99,184	109,357	
Household income	205.2			203.69	209.51	-5.82***
Household wealth	2784.07			2784.8	2818.21	-33.41***
Purchasing power	159.26			157.36	161.99	-4.63***
Single-family housing	0.91			0.92	0.97	-0.05***
Home owner status	8.4			8.46	8.49	-0.03***
Children count	0.54			0.54	0.58	-0.04***
Household head age	57.02			56.87	55.45	1.42***
Building year built	1964.75			1966.17	1967.67	-1.5***
(c) Black households:						
N of households	82,914			50,134	58,494	
Household income	84.7			100.79	110.22	-9.43***
Household wealth	1813.59			1968.54	2047.39	-78.85***
Purchasing power	63.33			75.44	83.18	-7.74***
Single-family housing	0.9			0.86	0.97	-0.11***
Home owner status	8.28			8.14	8.23	-0.09***
Children count	0.51			0.48	0.51	-0.03***
Household head age	56.01			54.29	53.63	0.66***
Building year built	1970.01			1973.48	1972.11	1.37***
(d) Hispanic households:						
N of households	29,639			18,527	31,463	
Household income	99.93			120.73	143.27	-22.54***
Household wealth	1751.06			2021.7	2182.79	-161.09***
Purchasing power	75.25			91.2	109.22	-18.02***
Single-family housing	0.88			0.83	0.96	-0.13***
Home owner status	8			7.91	8.18	-0.27***
Children count	0.38			0.42	0.43	-0.01
Household head age	48.35			49.79	50.8	-1.01***
Building year built	1959.54			1964.71	1964.47	0.24

Note: This table reports the mean values of demographic attributes of households in the sample used for estimating loan effects. The balance checks are also broken down by race in the treated group. The "Diff." column displays the difference between the treated and control groups, along with the corresponding p-value of the T-test. Significance levels are denoted by asterisks: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. After matching, demographic attributes are presented as weighted averages. The units of income, wealth, and purchasing power are expressed in thousands of dollars.

trends are observed in the pre-treatment period, either for the entire sample or for any specific racial group, thus providing support for the parallel trend assumption. More interestingly, the results indicate that most point estimates of treatment effect are higher for minority groups (Black and Hispanic) than for the White group both before and after matching.

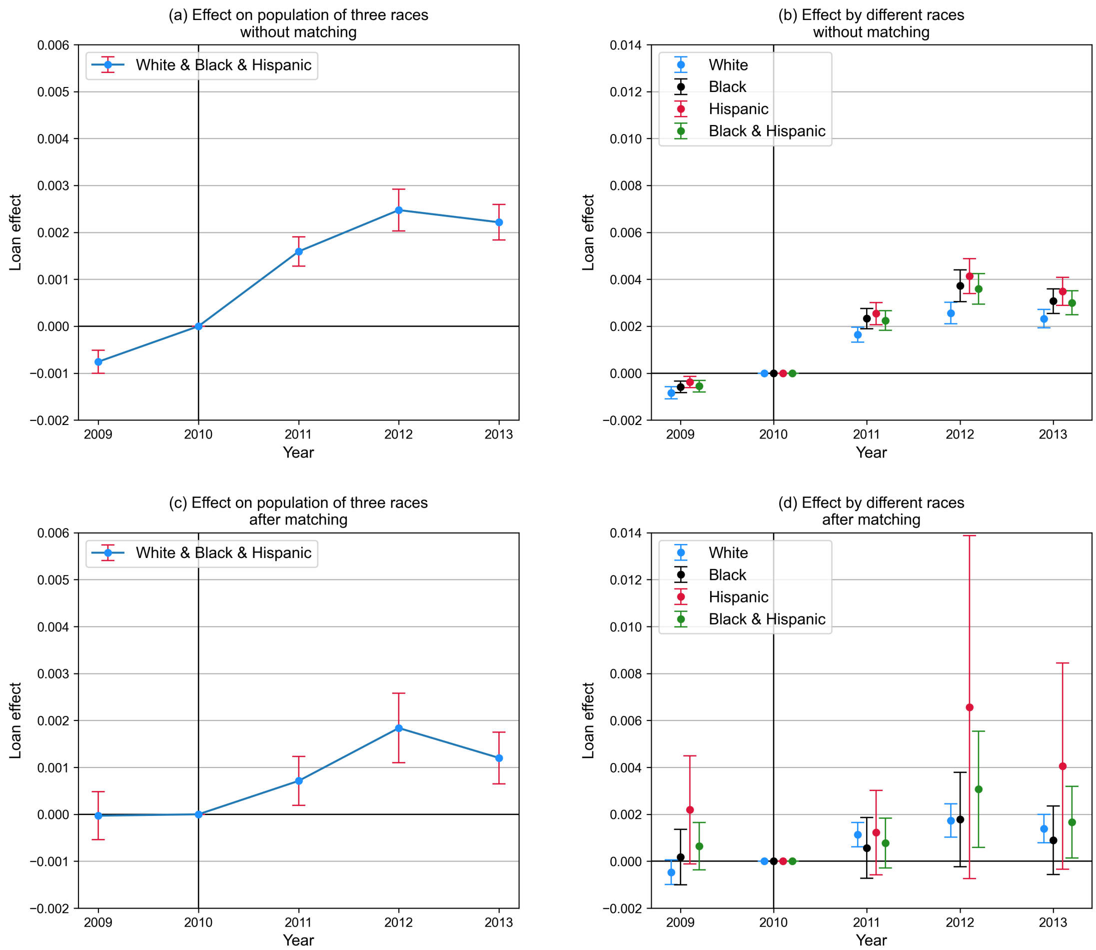

Figure 8: The event study of loan effect on heat pump adoption by racial groups. Note: The error bar is 95% confidence interval. In subplot (b), the control groups for all specifications consistently comprise all households from VA present in my sample. In subplot (d), for each treated racial group in MD, the corresponding control group consists of households in VA that have been matched based on observable covariates.

To formally estimate the disparity in loan effects across racial groups, I further employ a triple-difference estimator by running the following regression:

$$Y_{it} = \beta D_{it} + \theta D_{it} \times R_i + \delta Ng_{it} + \rho Elec_{it} + \alpha_t + \delta_i + \epsilon_{it} \tag{10}$$

where Y_{it} is a dummy outcome denoting the heat pump adoption status for household

i at year t; D_{it} is the treatment variable which takes the value of one only for treated households after the launch of loan program (since 2011)[9]; R_i indicates the racial identity of household i; Ng_{it} and $Elec_{it}$ are state-level yearly residential natural gas prices and utility-level residential electricity prices; α_t and δ_i are year fixed effects and household fixed effects. Standard errors are clustered at the household level. The coefficient of θ can be interpreted as the disparity in loan effects.

Table 6 reports estimates of the average effect and effect disparity of the loan program. Columns (1)-(3) present results without matching, while columns (4)-(6) present results with matching. All estimates are statistically significant, and the matching procedure does not alter the direction of the coefficients but does affect their magnitude. While the matching sample is smaller and more selective, it is more likely to satisfy the parallel trend assumption, making columns (4)-(6) the preferred specifications. The results in column (4) suggest that the loan program significantly increased the overall probability of heat pump adoption by 0.11%. In column (5), the loan's effect on minority populations is larger than on the White population by 0.02%, and this difference is statistically significant. Column (6) further indicates that this additional effect is equivalent between the Black and Hispanic populations at 0.02%. This suggests that the loan program is a progressive policy that reduced the racial gap in heat pump adoption, although the effect was limited.

A robustness check is also conducted by directly controlling for the 2010 SEEARP rebate amount in Equation 10, despite we observed pre-treatment parallel trends after matching (shown in figure 8). The rebate variable is assigned a value of 500 for MD residents in 2010 and 300 for VA residents in 2010, while all others are assigned a value of zero. Regressions are re-run for both the unmatched and post-matching samples. The findings, as shown in Table A.3, remain consistent.

The low-interest loan program provides two distinct types of incentives. Firstly, the reduced interest rate can be perceived as a form of subsidy, which effectively reduces the net present value of the costs of heat pump installation. Secondly, the loan program can alleviate credit and liquidity constraints faced by consumers. It is noteworthy that households belonging to Black and Hispanic communities tend to have significantly lower average incomes compared to White households. Consequently, they may rely more on the loan program to mitigate their credit and liquidity constraints. However, it is important to acknowledge that these minority or lower-income groups may encounter an information gap when seeking knowledge about the loan program. Due to systemic inequalities, some individuals might not have had the same access to educational resources, which could impact their understanding of the precise benefits provided by the low-interest loan program. The application process may also incur higher costs for these groups. In theory it is difficult to draw a conclusion regarding whether the loan program has a greater

[9] It is not necessary to worry about the bias from staggered treatment adoption in the DID estimator since every household was treated at the same time. (Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2020)

Table 6: The effect of loan program on heat pump adoption by racial groups

	DID			Matching + DID		
	(1)	(2)	(3)	(4)	(5)	(6)
Loan	0.0024***	0.0024***	0.0024***	0.0011***	0.0011***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Loan × Minority		0.0001***			0.0002**	
		(0.0000)			(0.0001)	
Loan × Black			0.0001***			0.0002**
			(0.0000)			(0.0001)
Loan × Hispanic			0.0001***			0.0002**
			(0.0000)			(0.0001)
Constant	0.0559***	0.0557***	0.0557***	0.0625***	0.0623***	0.0623***
	(0.0028)	(0.0028)	(0.0028)	(0.0065)	(0.0066)	(0.0066)
Electricity price control	Yes	Yes	Yes	Yes	Yes	Yes
Natural gas price control	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0003	0.0003	0.0003	0.0004	0.0004	0.0004
Number of observations	2,095,226	2,095,226	2,095,226	1,814,742	1,814,742	1,814,742
Number of households	426,026	426,026	426,026	367,143	367,143	367,143

Note: *** p<0.01, ** p<0.05, * p<0.1.The outcome is a dummy denoting the heat pump adoption status for household i at year t. Standard error is clustered at household level. The minority group referred to the Black and Hispanic populations in this analysis.

effect on the minority group, but the empirical results presented in this section provide evidence in favor of this proposition.

6.2 Racial inequality in access to rebate programs

Rebate programs are another commonly used incentive for heat pump adoption in the U.S. To examine the role of previous rebates in the adoption gap, this study analyzes data from the Massachusetts Clean Energy Center (MACEC) rebate program[10] and the State Energy-Efficiency Appliance Rebate Program (SEEARP) in SC, NC, VA, MD, DE, both of which provided rebates for residential air source heat pumps. Investigating both of these programs enhances representativeness as they cover a variety of climates, including warm, temperate, and cold conditions.

The Massachusetts Clean Energy Center data, which includes project addresses, installed heat pump system information, and rebate payment amounts for 20,094 recipients between 2014 and 2019, is matched with household demographic data sourced from

[10]The full name of this program is ”Residential & Small-Scale Air-Source Heat Pump Program”, implemented by the Massachusetts Clean Energy Center and funded by the Renewable Energy Trust Fund.

DataAxle. The recipients included 16,389 White households, 1,522 Asian households, 1,459 Hispanic households, and 376 Black households. On average, the rebate payment amount was approximately $600 per ton, and the total amount paid was 28 million dollars. The altered structure of rebate amounts across different years is presented in Table A.4 in Appendix A. Figure 9 illustrates the proportion of households who received the rebate, broken down by racial categories (see subplot (a)) and income quantiles (see subplot (b)). Two significant observations are apparent: a smaller proportion of Black and Hispanic households received rebates in comparison to White households; The rebate money was disproportionately channeled into the pockets of higher-income groups, despite the program's intention to provide higher rebate amounts per installed heat pump to lower-income households.

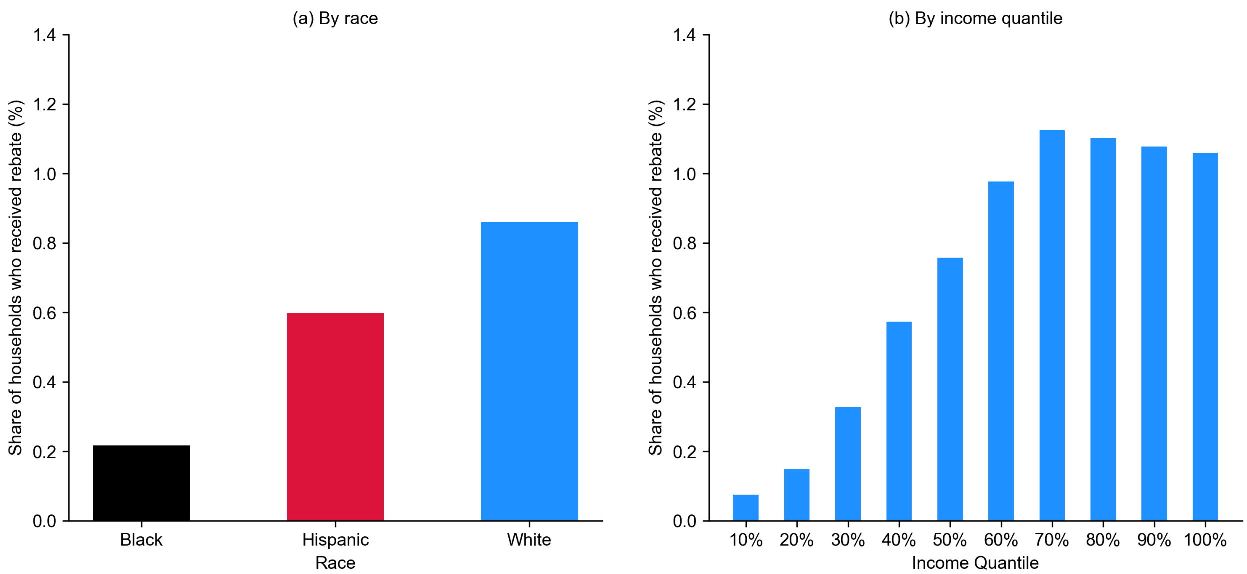

Figure 9: The share of households who received MACEC air source heat pump rebate in MA between 2014 and 2019. Note: In subplot (a), the denominator for each proportion represents the total number of households within each racial group in MA. In subplot (b), the denominator is the total number of households within each of the ten income intervals.

Furthermore, the SEEARP program in the other five states is also analyzed. The SEEARP program is a federal initiative that allocates funding to states, allowing them to design their own rebate schemes. In 2010, households in NC and VA were eligible for a rebate of $300 per air source heat pump system installed, while households in DE were eligible for a rebate of $400 per system, and households in SC and MD were eligible for a rebate of $500 per system. I retrieve the data from the Open Energy Data Initiative (OEDI), U.S. Department of Energy and it contains information on rebate payment amounts, and project ZIP codes, with a total of 12,184 residents receiving rebates for installing air source heat pumps in 2010. To examine the racial gap in accessing the SEEARP rebate, I regress the total amount of rebate payment at the ZIP code level on the percentage of Black, Hispanic, and Asian households, controlling for the total number of households, median household income, and fixed effects for either state or county. Notably, the percentage of White households was excluded from the model. Given that White, Hispanic, Black, and Asian populations comprise a substantial proportion of the population, the coefficients of the remaining variables can be interpreted as the relative effects compared to White households. The regression results (refer to Table A.5 in Appendix A) reveal that ZIP codes with a higher proportion of Black and Hispanic households received fewer rebates, regardless of controlling for median household income, state fixed effects, or county fixed effects.

In summary, the above descriptive evidence highlights an inequality in accessing the rebate program between different racial groups, which has the potential to further widen the gap in heat pump adoption. Two potential reasons can explain this disparity: Firstly, even with the small rebate, minority and lower-income groups may still face affordability challenges in adopting heat pumps due to credit/liquidity constraints and higher upfront installation costs, particularly as they tend to reside in older and economically disadvantaged buildings. Secondly, the minority and lower-income groups encounter difficulties in accessing information about the incentive programs, which further hinders their participation. Future studies can offer additional causal evidence on this matter.

7 Discussions

Existing literature has documented that low-income groups tend to exhibit lower adoption rates of clean energy technologies due to credit or liquidity constraints, information gaps, homeownership gaps, and other obstacles (Paulos 2017). On average, Black and Hispanic households possess lower income and wealth compared to White households. Furthermore, studies have demonstrated that minority groups display reduced adoption of clean energy technologies even after accounting for income and homeownership (Sunter et al. 2019). However, existing research has yet to identify the additional factors across racial groups that can elucidate this technology access gap. The empirical findings of this study reveal that, after controlling for income and wealth, Black and Hispanic households on average own older buildings compared to White households. Importantly, the decomposition analysis reveals that the building age disparity serves as the most crucial determinant of the heat pump adoption gap, surpassing the impact of income or wealth disparities.

The building age disparity, even when controlling for income and wealth, may be attributed to the enduring impact of historical discriminatory housing policies and practices in the U.S. One such policy, redlining, systematically denied mortgage financing to minority neighborhoods, leading to disinvestment and hindering their ability to acquire newer, more energy-efficient homes (Swope et al. 2022). Furthermore, zoning policies have often reinforced racial segregation by creating exclusionary zones that restrict the development of affordable housing or multi-family residences, limiting minority access to desirable housing options and perpetuating the building age disparity (Ellickson 2022). Housing market discrimination (Massey and Denton 1993) has also played a role in exacerbating the building age gap. Discriminatory practices, such as steering minority homebuyers towards older, less desirable neighborhoods, have restricted their access to newer, more energy-efficient homes (Galster 1990; Christensen and Timmins 2018). In addition, the suburbanization movement created a divide, as minorities were often left behind in older urban areas while new and more expensive housing developments emerged in suburban locations, predominantly catering to White populations (Jackson 1987). Moreover, intergenerational wealth accumulation has contributed to this disparity (Shapiro et al. 2013). Historically, White families have had greater opportunities to invest in real estate and pass their properties down to subsequent generations. As a result, they have been more successful in accumulating wealth through homeownership, enabling them to invest in newer properties and clean energy technologies like heat pumps.

This study's results highlight the importance of enacting targeted policy interventions that promote building retrofits, particularly in older structures where low-income minority populations are disproportionately represented. Older buildings are often characterized by poor insulation, antiquated ventilation systems, and limited electrical wiring, resulting in higher heat pump adoption costs and diminished future fuel savings for minority populations. Targeted initiatives, including income-based rebates for electric panel upgrades, electrical wiring enhancements, and weatherization interventions under the Inflation Reduction Act, contribute to the reduction of disparities in access to energy-efficient solutions. However, the current rebate and tax credit amounts—up to $7,100 for electric wiring and panel upgrades and up to $2,800 for weatherization measures—may not fully cover the expenses incurred in upgrading older buildings. Future research should investigate the distribution of building upgrade costs across various structures and demographic groups. Moreover, it is crucial to establish supplementary programs that specifically consider building age, income, and race to enhance energy equity. For instance, providing additional subsidies for low-income residents who own buildings exceeding a certain age threshold could be a viable strategy.

This study also sheds light on the interrelationship between climate, temperature, energy prices, and the heat pump adoption racial gap. The central idea is that the increased benefits of heat pumps create more motivation for people to adopt them, but minority groups face more challenges, such as higher upfront costs resulting from older buildings, credit constraints, and other factors. As a result, the macro environment that favors heat pumps can exacerbate the racial gap in heat pump adoption. Specifically, climate change is projected to affect the demand for heating and cooling differently across regions. In areas with a significant increase in heating and cooling demand or those that become more suitable for heat pump use, the incentives to adopt a heat pump will be greater, but it can also widen the heat pump adoption gap between different populations. On the other hand, the gradual phase-out of natural gas for heating would lead to higher fixed charges for utility gas service due to a dwindling customer base. The increase in natural gas prices, or even an outright ban, holds the potential to amplify the disparity in heat pump adoption further. This finding also carries implications for carbon pricing, a strategy that places a cost on burning fossil fuels, including natural gas, and is deemed the most efficient policy for reducing emissions. Nonetheless, carbon pricing is criticized for its adverse impacts on disadvantaged groups, a point corroborated by the results of this study.

Significant expectations have been pinned on public policy to promote the adoption of heat pumps and address the adoption gap across different groups. Previous rebate programs have generally offered small rebates for air source heat pumps, like the two programs examined in this study, which provided rebates ranging from $100 to $600 per ton. Particularly, although the MACEC rebate program was specifically designed to provide larger rebates to lower-income groups, the majority of rebate recipients are higher-income groups that exceed 120% of the state median income. This discrepancy may arise from the fact that lower-income households still face challenges in affording heat pumps even with the relatively higher small rebate, or they may lack access to information about the program. Consequently, these small rebate programs have been found to be regressive and have the potential to exacerbate the racial gap in heat pump adoption. However, the current electrification rebate, in conjunction with tax credits under the 2022 Inflation Reduction Act, can provide lower and medium-income groups with up to $10,000 for air source heat pumps, while excluding high-income groups from receiving the rebate. Since this rebate can cover almost the entire cost of heat pump adoption, all low-income residents are eligible to apply for it, making it a progressive policy. However, the current budget of the Inflation Reduction Act can only fund a limited number of households, and it is unclear whether this policy will be sustainable in the future due to the high policy costs. In contrast, low-interest loan programs can offer a lower public budget burden while also having the potential to alleviate the racial gap in heat pump adoption based on the finding of this paper. Therefore, future policies can consider providing more loan programs to support heat pump adoption.

Appendices

A Appendix Tables

Table A.1: Correlation between DataAxle and U.S. Census data

State	White Corr.	Black Corr.	Asian Corr.	Hispanic Corr.	Median Income Corr.
SC	0.972	0.760	0.879	0.908	0.817
NC	0.964	0.771	0.965	0.962	0.771
VA	0.971	0.801	0.977	0.979	0.854
MD	0.968	0.925	0.980	0.981	0.832
DE	0.964	0.745	0.963	0.971	0.847
PA	0.987	0.937	0.955	0.992	0.736
CT	0.973	0.829	0.918	0.983	0.905
RI	0.980	0.952	0.901	0.982	0.726
MA	0.978	0.860	0.976	0.959	0.875

Note: Using the DataAxle dataset, I compute the median household income at the ZIP code level, along with the percentage of households belonging to various ethnic groups. Subsequently, I calculate the Pearson's correlation coefficients between these figures and the ZIP code-level estimates from the 2021 U.S. ACS data.

Table A.2: Impact of natural gas price change on homeowners' heat pump adoption by race

	(1) All	(2) White	(3) Hispanic	(4) Black
log(natural gas price)	0.016***	0.019***	0.011***	0.004***
	(0.0003)	(0.0003)	(0.0012)	(0.0011)
4th polynomials of elec price	Yes	Yes	Yes	Yes
4th polynomials of HDD	Yes	Yes	Yes	Yes
4th polynomials of CDD	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
R-squared	0.0089	0.0098	0.004	0.005
Number of observations	28,594,453	23,509,068	1,689,739	3,395,646
Number of households	3,496,158	2,903,003	200,827	392,328

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The outcome is a dummy indicates new heat pump adoption for each year. The model includes households owned by residents located in natural gas utility service territories in South Carolina, North Carolina, Virginia, Maryland, and Delaware. Column (1) includes households from the three racial groups.

Table A.3: Robustness check: The effect of loan program on heat pump adoption by racial groups

	DID			Matching + DID		
	(1)	(2)	(3)	(4)	(5)	(6)
loan	0.0029***	0.0029***	0.0029***	0.0012***	0.0012***	0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0004)
Loan × Minority		0.0001***			0.0002**	
		(0.0000)			(0.0001)	
Loan × Black			0.0001***			0.0002**
			(0.0000)			(0.0001)
Loan × Hispanic			0.0001***			0.0002**
			(0.0000)			(0.0001)
Constant	0.0495***	0.0493***	0.0493***	0.0610***	0.0608***	0.0608***
	(0.0029)	(0.0029)	(0.0029)	(0.0064)	(0.0065)	(0.0065)
Rebate control	Yes	Yes	Yes	Yes	Yes	Yes
Electricity price control	Yes	Yes	Yes	Yes	Yes	Yes
Natural gas price control	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004
Number of observations	2,095,226	2,095,226	2,095,226	1,814,742	1,814,742	1,814,742
Number of households	426,026	426,026	426,026	367,143	367,143	367,143

Note: *** p<0.01, ** p<0.05, * p<0.1.The outcome is a dummy denoting the heat pump adoption status for household i at year t. These regressions directly control for the 2010 SEEARP rebate amount. The rebate variable is assigned a value of 500 for MD residents in 2010 and 300 for VA residents in 2010, while all others are assigned a value of zero. Standard error is clustered at household level. The minority group referred to the Black and Hispanic populations in this analysis.

Table A.4: Rebate Amounts in Massachusetts Clean Energy Center - Residential & Small-Scale Air-Source Heat Pump Program

Year	Rebate amount
2014	$750 per system or ton
2015	$750 per system or ton
2016	base: $625 per system/ton; under 120% state median income: $750 per system/ton; under 80% state median income: $1,500 per system/ton
2017	base: $625 per system/ton; under 120% state median income: $800 per system/ton; under 80% state median income: $1,000 per system/ton
2018	base: $625 per system/ton; under 120% state median income: $800 per system/ton; under 80% state median income: $1,000 per system/ton
2019	base: $500 per system/ton; under 120% state median income: $750 per system/ton; under 80% state median income: $1,000 per system/ton

Note: The rebate amount for single-head heat pumps was per system. For central or multi-head heat pumps, the rebate amount was calculated per ton, which is equivalent to 12,000 BTU/hr. Residents who received electric service from Eversource, National Grid, Unitil, or an eligible municipal light plant were eligible to apply for the rebate.

Table A.5: The racial gap in accessing SEEARP rebates in SC, NC, VA, MD, DE in 2010

	Outcome: Total amount of rebate payment ($) at ZIP level					
	(1)	(2)	(3)	(4)	(5)	(6)
Black household %	-28.86***	-16.92***	-30.21***	-20.73***	-41.05***	-34.74***
	(3.15)	(2.98)	(3.25)	(3.13)	(5.28)	(5.33)
Hispanic household %	-124.99***	-115.88***	-94.32***	-89.88***	-66.70***	-51.46***
	(18.08)	(17.51)	(16.14)	(15.99)	(15.16)	(14.72)
Asian household %	117.60***	-14.10	56.55	-43.71	15.07	6.45
	(36.07)	(37.16)	(34.95)	(36.92)	(39.67)	(40.79)
Number of households	0.45***	0.45***	0.48***	0.47***	0.45***	0.45***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Median Household Income		0.04***		0.03***		0.02***
		(0.00)		(0.00)		(0.01)
Constant	774.72***	-1245.64***	-548.75*	-2573.80***	-475.06	-1620.55***
	(80.30)	(220.15)	(314.28)	(430.80)	(386.84)	(509.76)
State FE	No	No	Yes	Yes	No	No
County FE	No	No	No	No	Yes	Yes
R-squared	0.25	0.28	0.30	0.33	0.59	0.59
Number of observations	2,600	2,572	2,600	2,572	2,586	2,560

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. To examine the racial gap in accessing the SEEARP rebate, I regress the total amount of rebate payment at the ZIP code level on the percentage of Black, Hispanic, and Asian households, controlling for the total number of households, median household income, and fixed effects for either state or county. Notably, the percentage of White households was excluded from the model. Given that White, Hispanic, Black, and Asian populations comprise a substantial proportion of the population, the coefficients of the remaining variables can be interpreted as the relative effects compared to White households.

B Appendix Figures

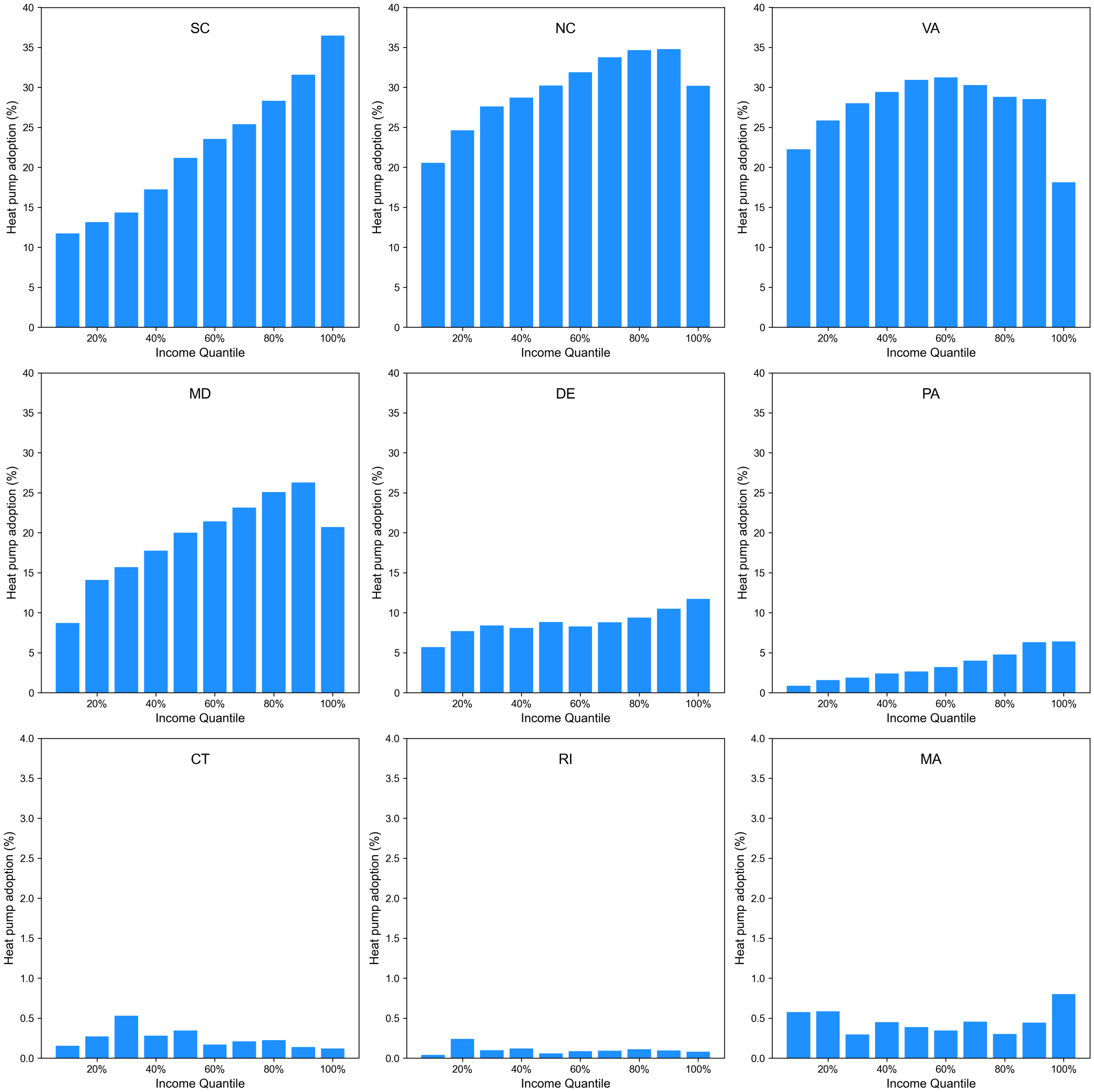

Figure B.1: Heat pump adoption percentage by income in nine U.S. East Coast states in 2021. Sources: Corelogic, DataAxle.

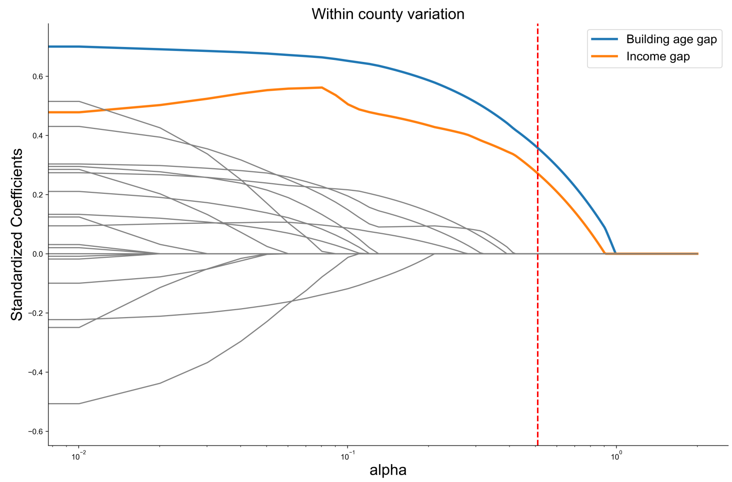

Figure B.2: Lasso coefficients as function of alpha using within county variation.

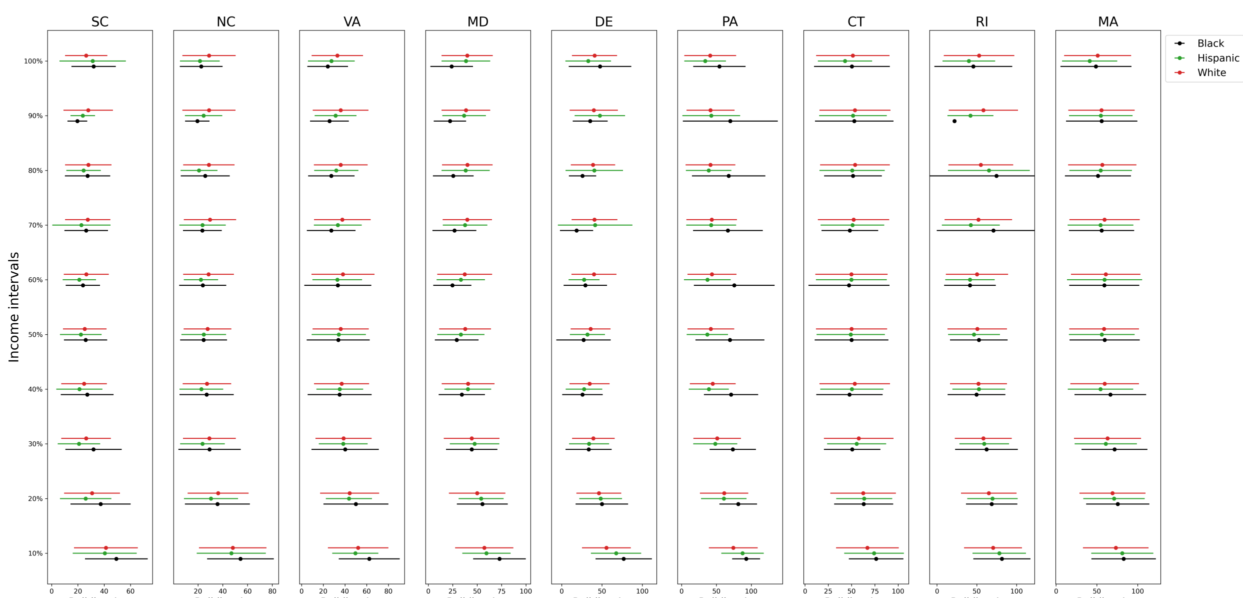

Figure B.3: The average and standard deviation of building age by race and income in 2021, categorized by the nine states.

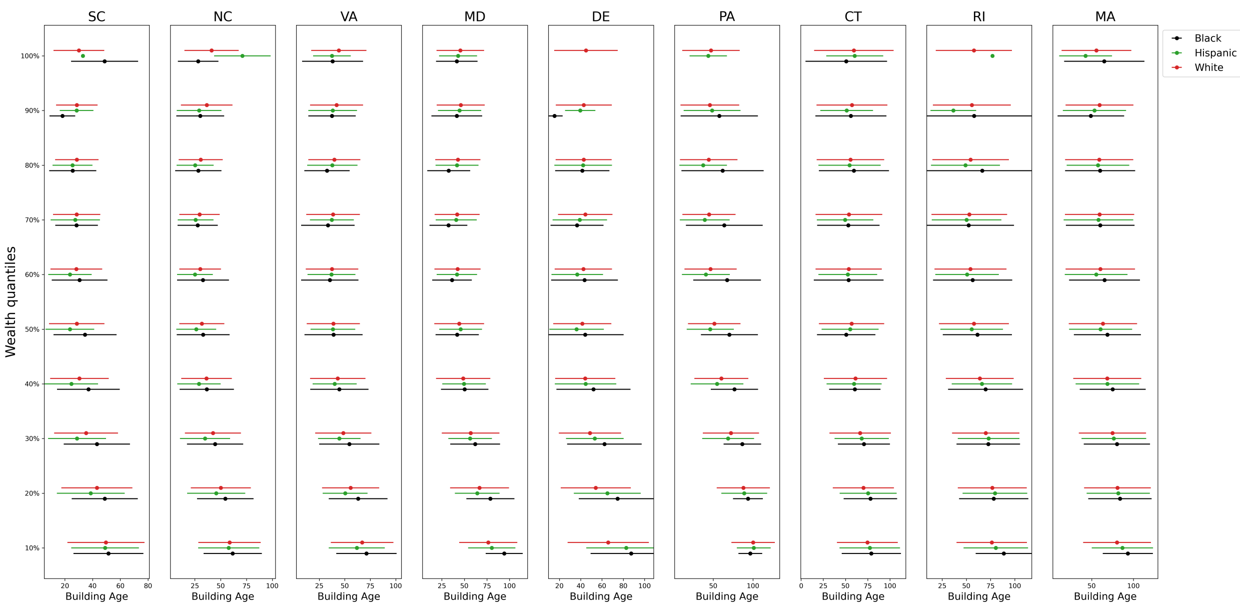

Figure B.4: The average and standard deviation of building age by race and wealth in 2021, categorized by the nine states.

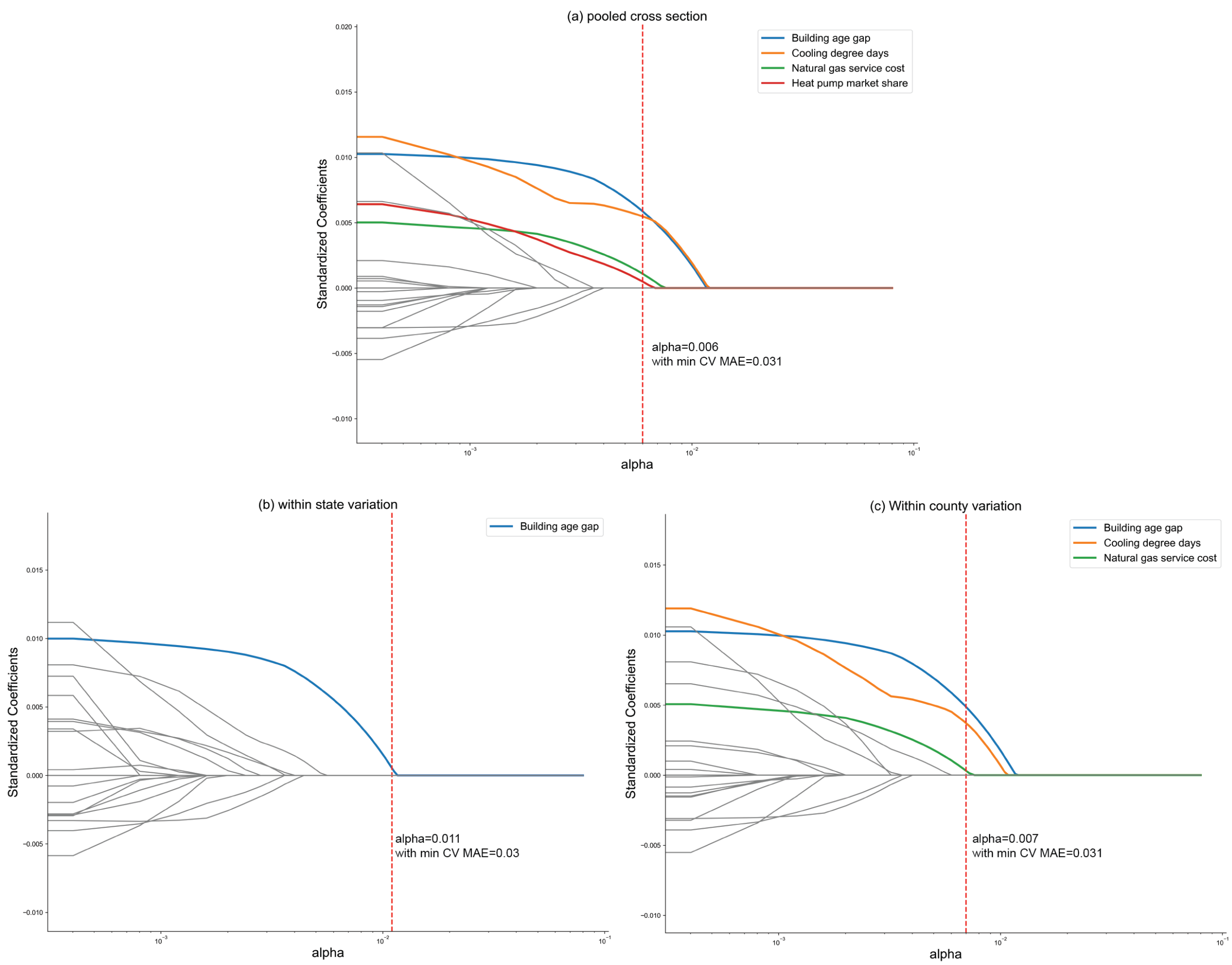

Figure B.5: Robustness check: Lasso coefficients as function of alpha during variable selection. Note: Simple differences are employed to measure the gap in heat pump adoption rate and related socio-demographic characteristics.

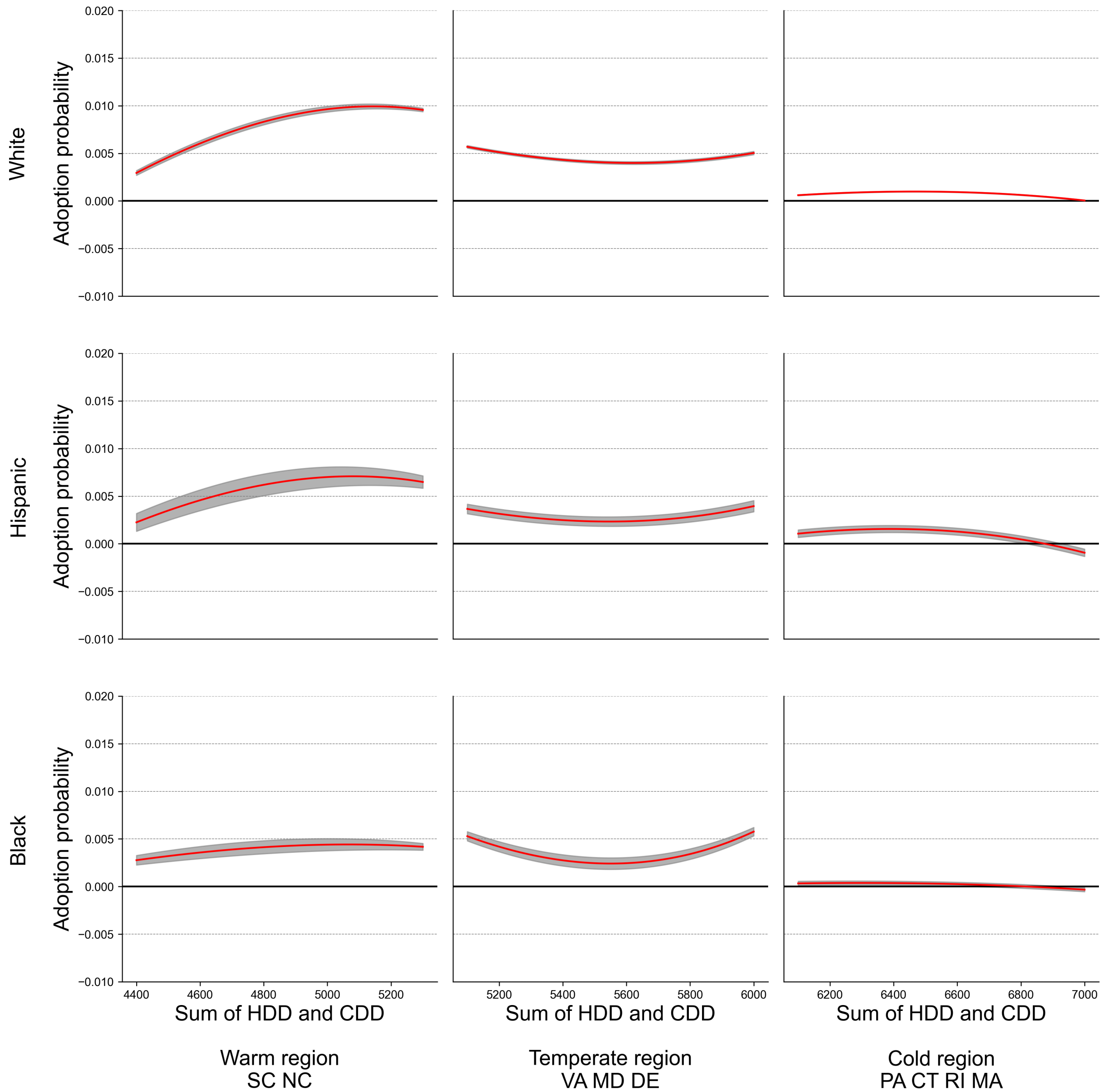

Figure B.6: The impact of the sum of heating and cooling degree days on the adoption probability of heat pumps by race and region. Note: Gray shaded areas are 95% confidence intervals.

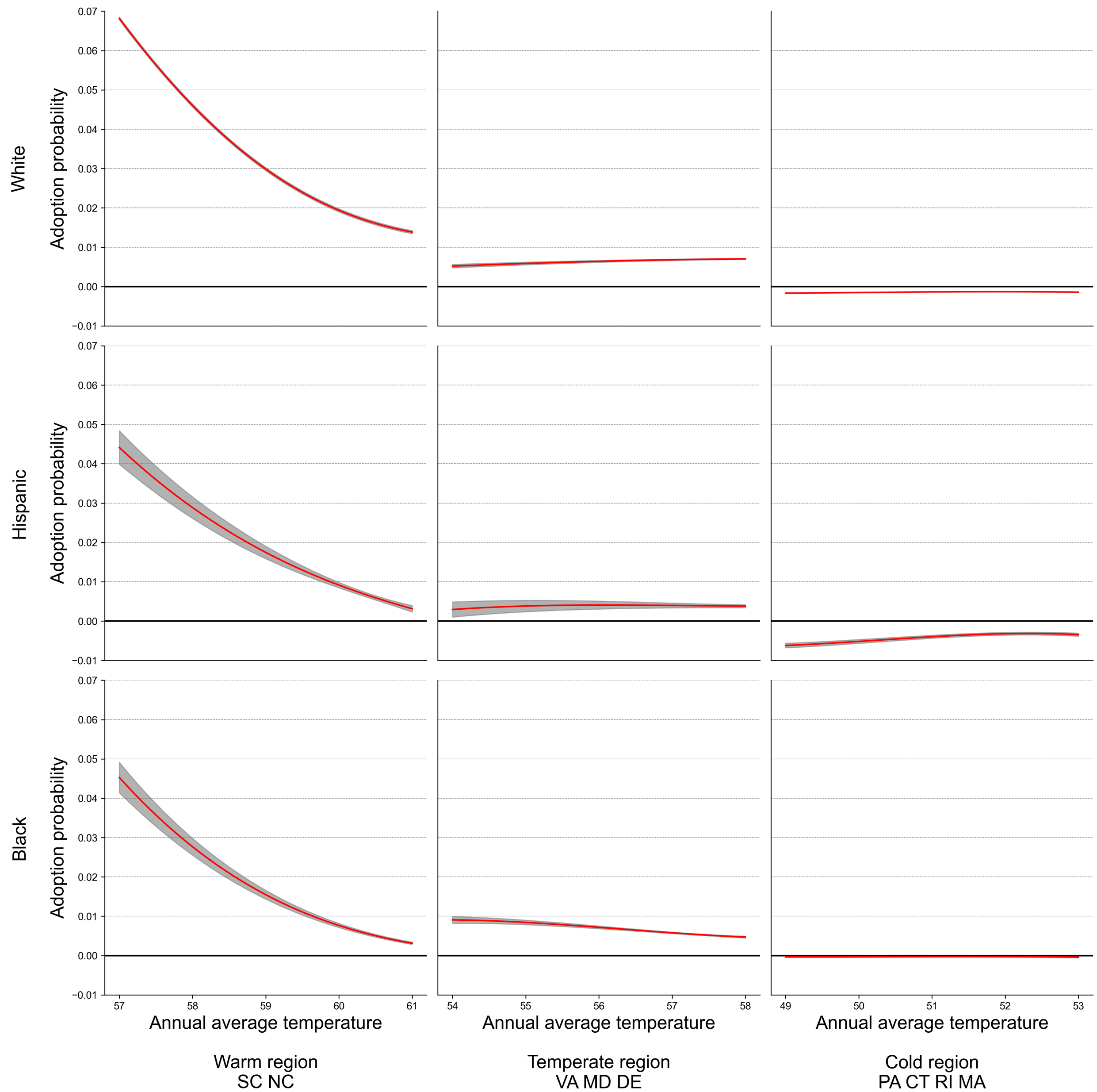

Figure B.7: The impact of annual average temperature (°F) on the adoption probability of heat pumps by race and region. Note: The sample includes homeowners only. Gray shaded areas are 95% confidence intervals.

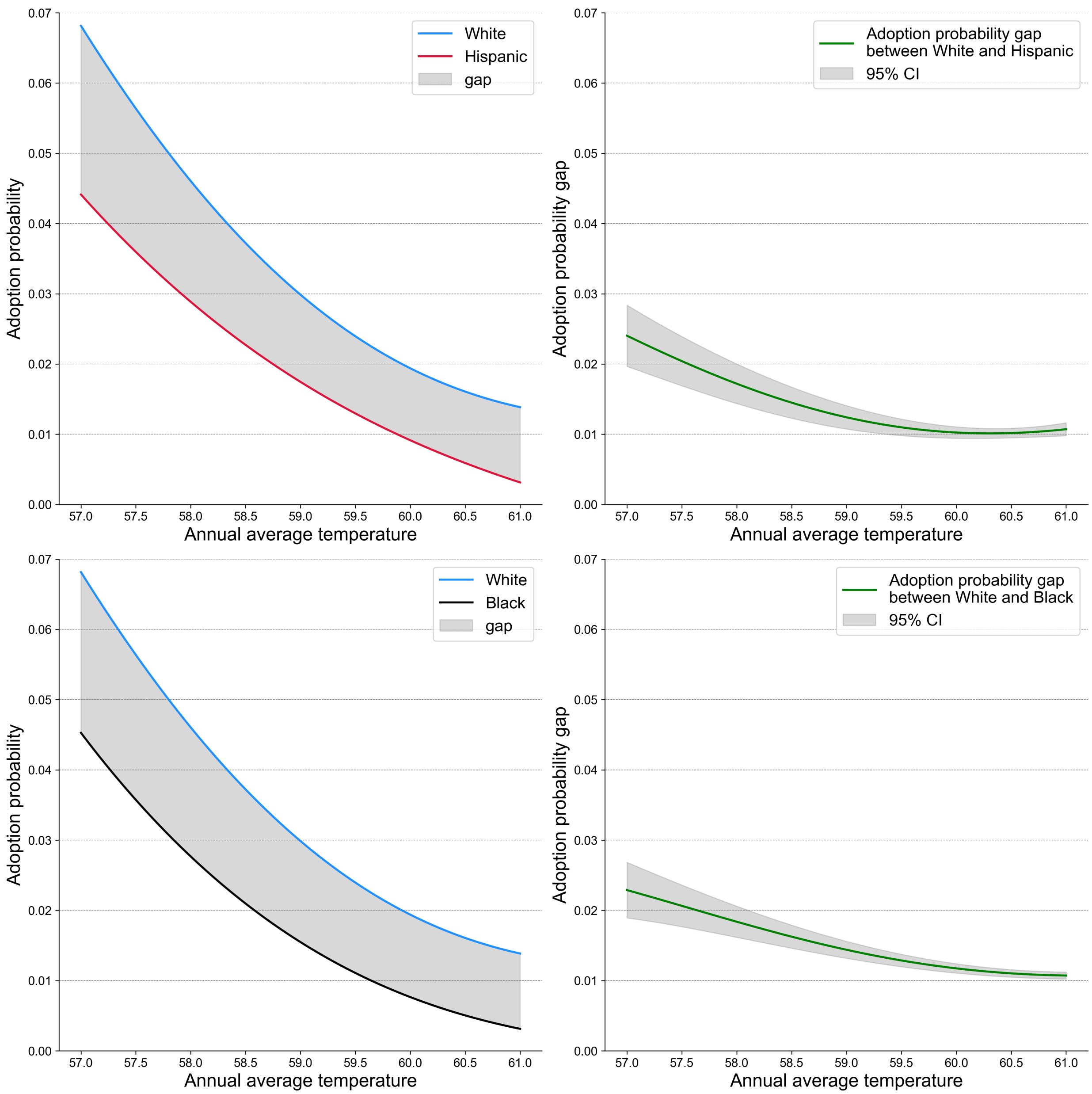

Figure B.8: The association between temperature change and heat pump adoption probability gap in NC and SC. Note: the sample includes homeowners only.

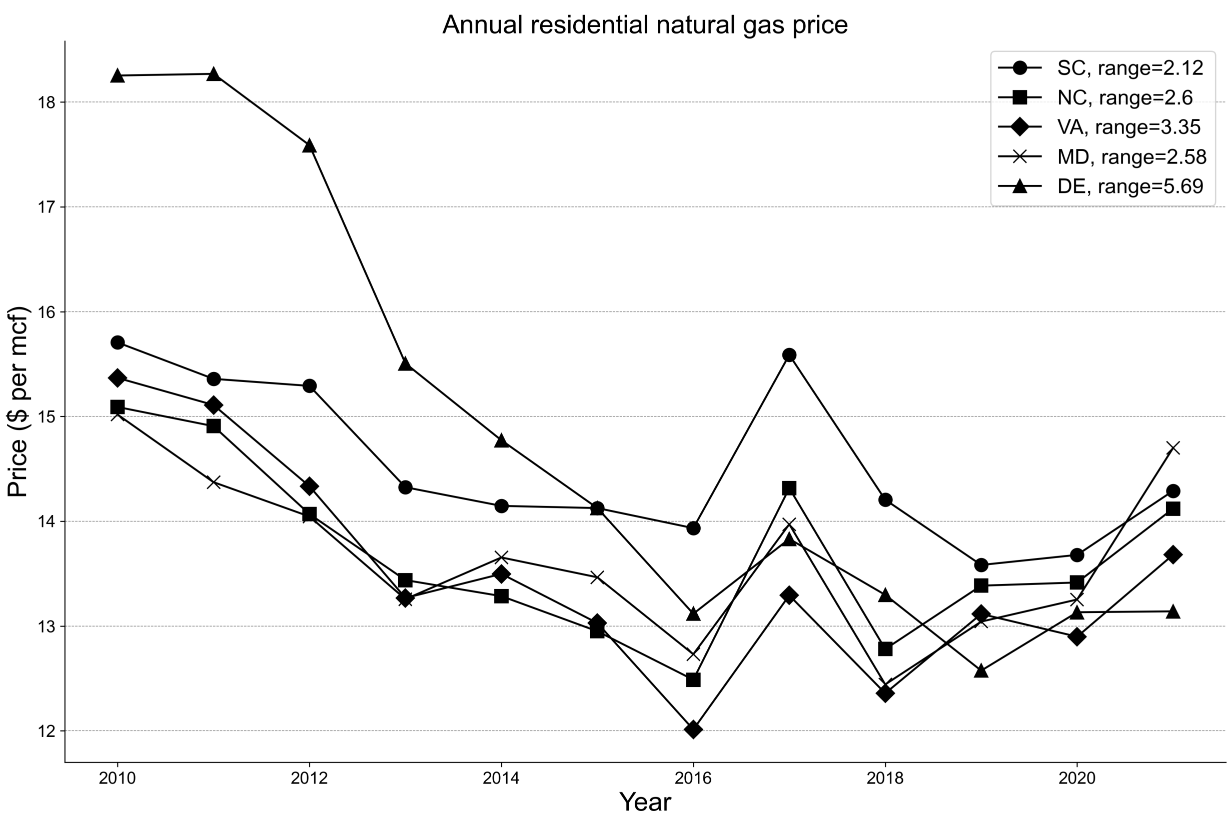

Figure B.9: Trends in residential natural gas prices in South Carolina, North Carolina, Virginia, Maryland, and Delaware (2010-2021)

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