Assessing inequities in electrification via heat pumps across the U.S.

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Abstract

Electrifying space heating is essential to reduce greenhouse gas emissions from the building sector, and heat pumps have emerged as an energy-efficient and increasingly cost-effective solution. However, other clean energy technologies (e.g., rooftop solar) are less common in underserved communities, and thus policies incentivizing their adoption can be regressive. Unlike previously-studied technologies, the effects of heat pumps on energy bills may be positive or negative, and thus inequities in their access are context specific. Here we propose a framework for identifying inequities in heat pump access and map these inequities across the U.S. We find that households in communities of color and with high percentages of renters have access to heat pumps at lower rates across the board, but differences are largest in areas where heat pumps are likely to reduce energy bills. Public policies must address these inequities to advance beneficial electrification and energy justice.

Main Paper

1. Introduction

Policy responses to the climate crisis are expanding rapidly in the U.S. at national, state, and local levels.[1] Research suggests that carbon dioxide (CO_2) emissions must decline dramatically over the next decade and reach net zero by mid-century to limit global temperature change to well below 2°C, and preferably 1.5°C, as set out in the Paris Agreement.[2] Strategies to meet these targets in the energy sector include two key elements: (1) transitioning electricity generation to low-carbon technologies such as wind and solar and (2) electrifying energy needs in transportation, industry, and buildings. Transitioning buildings off natural gas (and other fuels such as propane, heating oil, and wood) and electrifying space heating needs is essential to reducing emissions from the building sector. Natural gas emits CO_2 when it is burned in home

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appliances and also leaks throughout the supply chain.[3,4] Unburned natural gas is primarily methane, a potent greenhouse gas.[5] A transition away from natural gas to all-electric appliances in buildings is thus essential to meeting net zero and other climate policy goals.[6]

Heat pumps are an attractive option for electrifying space heating that operate by transferring heat between indoor and outdoor air (see Section 1 of the Supplementary Information). They can be roughly 3-5 times as efficient as traditional electric resistance heaters and provide heating in the winter and cooling in the summer.[7] Over 10% of U.S. households use heat pumps as their primary source of heating today, and the market share is growing rapidly globally.[8,9] Homes with heat pumps also enjoy a price premium when they are sold.[10] The net private and social benefits of heat pumps depend on many factors including local climate, electricity mix, energy prices, installation costs, and the insulation and air-tightness of a building. Heat pumps are cost effective in many locations across the U.S., with highest benefits in areas with mild climates and inexpensive electricity.[8,11,12] However, in some colder regions where they are less efficient, they can have higher operating costs, especially compared to natural gas furnaces. Nevertheless, high heat pump use rates (up to 90%) are likely to reduce greenhouse gas emissions and provide other benefits as the electric grid continues to decarbonize.[13]

There is a strong rationale for public policy to support heat pumps. The net social benefits on a national scale are positive, yet there are many barriers to access.[14–16] A rich literature on the energy efficiency gap identifies barriers for other technologies that likely apply to heat pumps,[17] including high upfront costs, credit and liquidity limitations, low familiarity with technologies,[8] low awareness of policy incentives,[17,18] personal preferences or behavioral factors,[19] and limited financial and engineering literacy.[20] Split incentives for rental units[21] or homeowners who may wish to move in the future[22] also hinder adoption. A variety of policies have been proposed to address these barriers.[10] The Inflation Reduction Act (IRA) substantially expands incentives at a federal level,[23] and local, state, and utility policies are increasingly promoting electrification (see Section 2 of the Supplementary Information). However, underserved households may be less likely to take advantage of these policies.[24] If heat pumps provide direct benefits to households (e.g., by reducing energy bills), these differences may exacerbate existing inequities in the energy system.[25] Furthermore, as electrification continues, households that electrify sooner are less likely to bear the burden of stranded assets as the transition accelerates.[26]

Here we investigate how different communities across the U.S. experience one element of the energy transition: electrification via heat pumps. Specifically, we explore spatial patterns in heat pump access across the U.S. to inform the design of equitable energy policies. Although space heating and cooling represent on average 55% of household energy use and 44% of energy bills (with high regional variation[27]), inequities in heat pump access have yet to be explored. Assessing inequities in the heat pump market also presents a distinct conceptual and analytical challenge compared to technologies such as rooftop solar and energy efficiency because operating costs are highly variable and may exceed the costs of fossil fuel alternatives, even if installation is free. We develop a framework for evaluating inequities in this class of technologies and apply it to heat pumps using a large, national property dataset and local socioeconomic data (see Methods). Specifically, we address the following questions: (1) How does heat pump

access across the U.S. vary with respect to income, race/ethnicity, and renter status? (2) Where do these access patterns suggest possible inequalities (and where do they not)? (3) What are the implications for public policies to promote fair and just energy transitions?

2. Framework for estimating heat pump inequities

Energy justice calls for everyone to have access to clean, safe, affordable, and reliable energy infrastructure and to be able to participate in energy decisions that affect them.[28,29] However, researchers and communities have identified injustices throughout the energy life cycle.[29–32] Underserved communities are simultaneously more likely to experience energy-related pollution and less likely to experience the benefits of energy services.[33] Energy poverty remains a key policy challenge in the U.S., with one in three households reporting difficulty paying energy bills.[34] Households experiencing energy poverty may limit their energy use,[35] forgo other essential services to pay energy bills, or experience shut-offs if bills are not paid.[36] They are also more vulnerable to shocks (e.g., COVID-19[37]), changes in energy prices,[38] and the effects of extreme weather.[39] Households in communities of color are significantly more likely (~60%) to be energy burdened compared to those in majority white communities.[15] They are also more likely to live in energy-inefficient homes and less likely to have access to clean energy technologies like rooftop solar, even after controlling for income and resource potential.[16,17]

Our framework for assessing inequities in heat pump access explores disparities in communities' experiences of the clean energy transition by distinguishing between three concepts: inequality, inequity, and injustice (see Figure 1). *Inequality* refers to a difference in access across populations.[40–42] Inequalities have many potential drivers and do not necessarily indicate a need for policy intervention. Specifically, we expect to see more heat pumps in mild climates, where they are more efficient and cost-effective.[13] However, differences may persist even after controlling for these factors. Specifically, there may be lower access in underserved communities (e.g., racial or ethnic minorities, low-income households, and renters). Previous literature on other clean energy technologies (e.g., rooftop solar) characterizes these differences as a form of *inequity*.[24,30,43,44] Inequity is a normative concept that refers to what is considered unfair, with roots in philosophical and legal scholarship.[45] If a technology provides benefits to households (e.g., by reducing energy bills), it is unfair for underserved households not to have equal or greater access to the technology. Finally, we refer to *injustice* as a case where policies or other systemic factors exacerbate, or perpetuate, existing inequities (see Discussion).
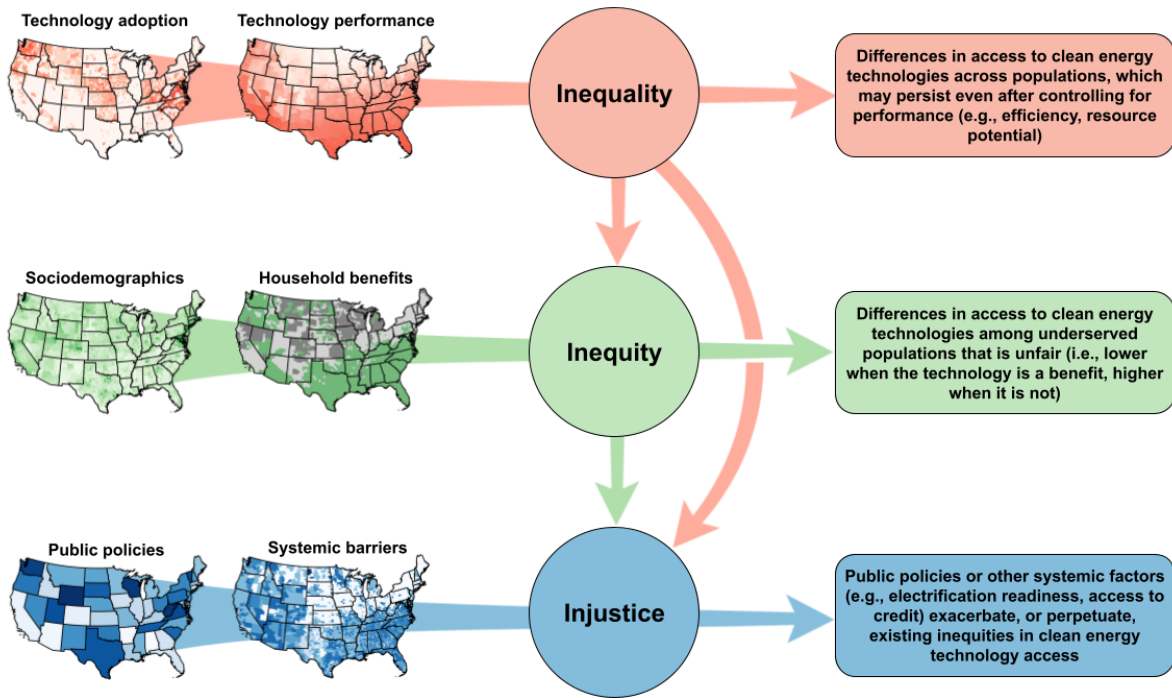
Figure 1. *Framework for assessing inequalities, inequities, and injustices in clean energy technologies whose benefits to households may be positive or negative. First, we use spatial data on different technology types and performance to assess inequalities in access. Second, we add in data on sociodemographics and the household benefits to determine if these inequalities are also inequities. Third, this framework can be further applied to identify injustices where public policies or other systemic barriers are exacerbating or perpetuating inequities. We use this framework to assess inequalities and inequities in heat pump access in this paper.*

Many clean energy technologies, such as energy efficiency and rooftop solar, provide benefits to households by reducing energy bills. Heat pumps, in contrast, may raise or energy lower bills depending on their efficiencies, energy prices, and other factors. Lower heat pump access among underserved households in areas where they lower bills (or provide other benefits) represents a potential inequity. It may suggest that there are disproportionate (and thus unjust) barriers to access for these households, and that public policies incentivizing heat pumps are regressive (and thus unfairly burden low-income households). However, higher access among underserved households in areas where heat pumps raise bills also represents a potential inequity. For these cases, heat pump adoption among relatively advantaged (e.g., wealthier) populations can provide an important service to society by buying down the cost curve. To operationalize this framework and capture these two different types of inequity, we integrate spatial data on heat pumps and other heating technologies and a cost/benefit model of energy bill impacts. We then assess patterns in heat pump access overall and across regions where they are likely to cause energy bills to increase, decrease, or stay the same.

3. Patterns in heat pump access across the U.S.

Heat pump access varies substantially across the U.S., as does the use of electricity, natural gas, and other heating fuels (see Figure 2). As heat pump use is not reported with high granularity in public databases, we use a national cross-sectional household property data from the Zillow Transaction and Assessment Database (ZTRAX).[10,46] We develop a logistic regression (logit) model to predict household-level access as a function of census-tract-level variables. Using this model, we assess whether differences in race, ethnicity, income, and renter status significantly predict differences in the likelihood of household heat pump access. We also control for factors expected to predict access such as heating and cooling degree days (HDD and CDD, which affect efficiency), electricity and natural gas prices, and building age (as a proxy for electrification readiness) and type. Finally, we include state dummy variables to account for state-level policies (such as electrification subsidies or fuel-switching restrictions) and other state-specific differences. (See Methods and Section 3 of the Supplementary Information for a full description of data sources.)

a

0%
>0% - 5%
5% - 10%
10% - 20%
20% - 40%
40% - 80%
80% - 100%

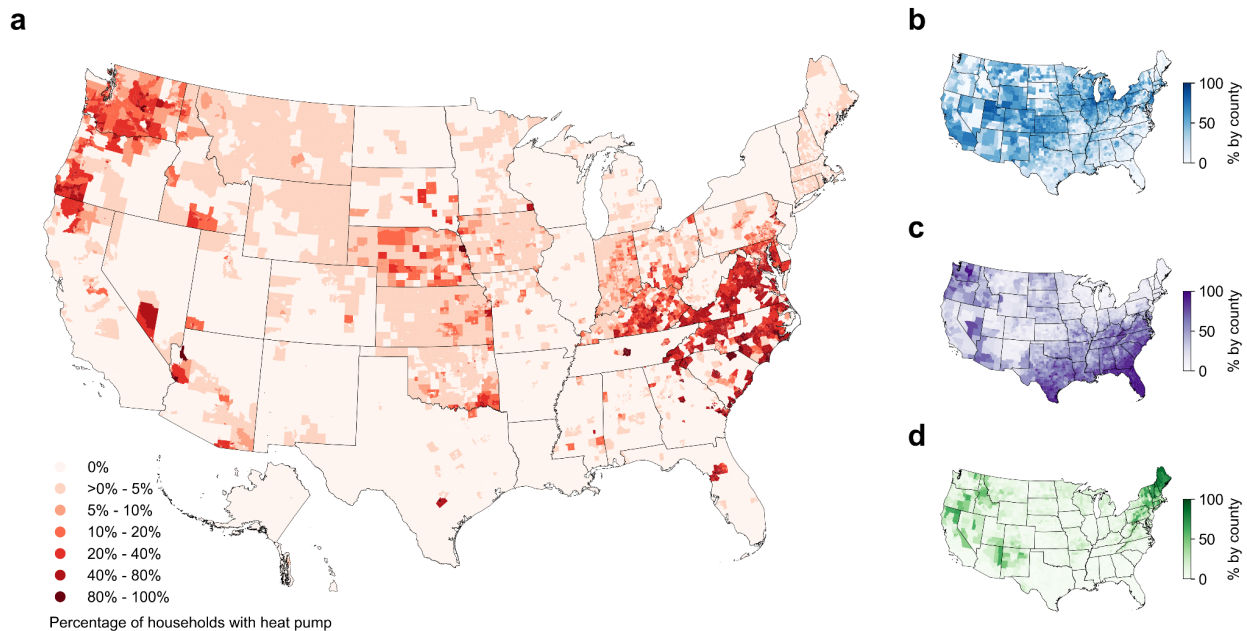Percentage of households with heat pump

b

c

d

Figure 2. Patterns in heating technology access across the U.S. (a) Percentage of households with a heat pump at the census tract level from the Zillow Transaction and Assessment Database (ZTRAX) in 2020. (b-d) Household heating technology at the county level from the American Community Survey (ACS) 5-year (2016-2020) data: (b) natural gas, (c) electricity (which includes heat pumps and electric resistance heating), and (d) other fuels. (Note that some counties do not report heating technology in ZTRAX. We discuss missing data in the Methods.)

As expected, we find that our control variables significantly predict heat pump access (see Figure 3a).[18] After controlling for state effects, we find a negative relationship between the odds of heat pump access and both HDD and CDD (with a standard deviation increase in HDD/CDD corresponding to a 41% and 16% decrease, respectively, in odds). This effect is likely explained

by the better performance of heat pumps in mild climates. There is also a large negative relationship between building age and heat pump access (additional analysis suggests a nonlinear relationship; see Section 9.7 and Figure S1 of the Supplementary Information). This conforms with the theory that older buildings are generally less well insulated and less well equipped to handle heat pump installations. We also find that higher electricity prices are associated with higher odds of heat pump access (with a standard deviation increase in price corresponding to a 24% increase in the odds). This may be explained by the larger number of heat pumps in areas where electric resistance heating is common, where higher electricity prices provide a greater incentive to switch to more efficient heat pumps. We find that natural gas prices are much less predictive (a standard deviation increase is associated with a 2% decrease in the odds). Similarly, we find only a small positive relationship with home value.
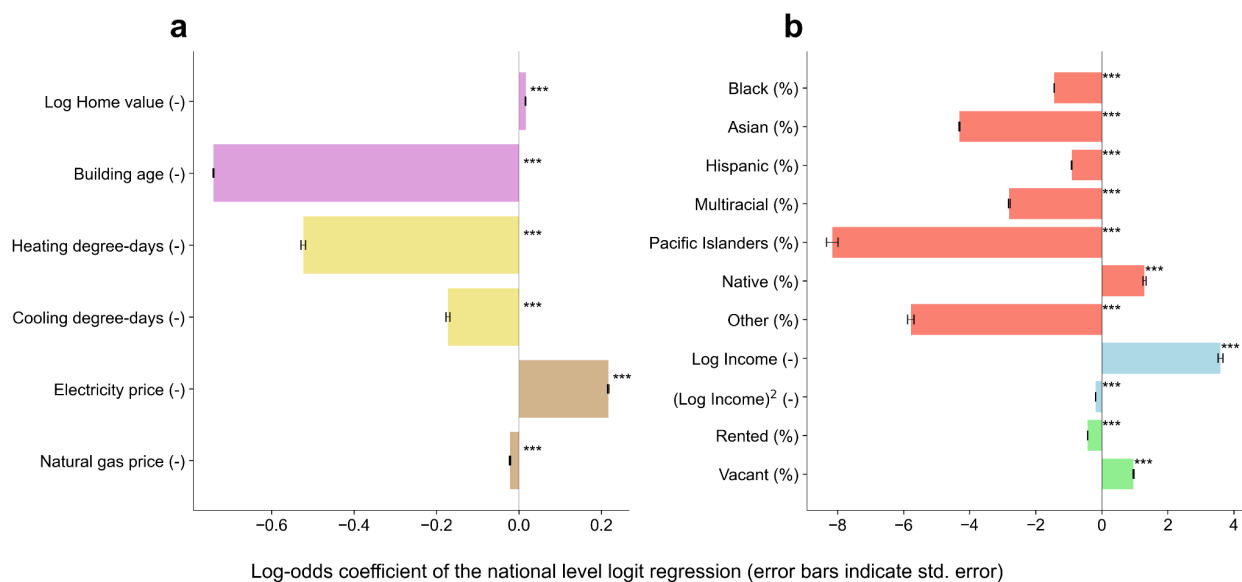

Log-odds coefficient of the national level logit regression (error bars indicate std. error)

Figure 3. *Factors associated with heat pump access across the U.S. Log odds coefficients of (a) the control variables for the logistic regression and (b) the equity-related variables. HDD, CDD, building age, and electricity and natural gas prices are normalized (i.e., one unit represents a one standard deviation change). Standard deviations are: 2093 °F-day (HDD), 1022 °F-day (CDD), 22.21 years (building age), 0.04 $ per kWh (electricity prices), and 3.62 $ per thousand cubic foot (natural gas prices). Symbols indicate: *** p<0.01, ** p<0.05, * p<0.1. See Section 8 of the Supplementary Information for more explanation of the interpretation of log odds coefficients.*

After controlling for these predictors, sociodemographic variables still strongly predict heat pump access (see Figure 3b). The percentage of minority households (with the exception of Native American) in a census tract significantly predicts lower odds of heat pump access. For example, a 10% increase in the Black population in a census tract is associated with a 13% decrease in the odds of heat pump access. The percentage of Asian, multiracial, Pacific Islander and other non-white racial/ethnic identities are also significantly and negatively associated with heat pump access relative to white populations. Coefficients for income and its square suggest a non-linear effect of income on heat pump access, which we explore in the next section (and Section 10 of

the Supplementary Information). Additionally, a 10% increase in renter-occupied units in a tract is associated with a 4% decrease in the odds of heat pump access. These results are robust to a variety of different model formulations (see Section 9 of the Supplementary Information). We also performed an analysis with a smaller dataset with household-level demographic data from the Residential Energy Consumption Survey (RECS), which yielded similar results (see Section 6 of the Supplementary Information).

4. Nonlinear predictors of heat pump access

We also explore non-linear relationships between heat pump access (normalized by state), median income, and the percentage of homes rented across different racial/ethnic majority census tracts (see Methods and Figure 4). Households of color are disproportionately low-income and more likely to be renters, but distinct patterns emerge when comparing census tracts with similar median income and homeownership rates.[47,48] We find substantial variation in access across racial/ethnic groups and in its relationship with income and renter status. For white-majority census tracts (69% of tracts), heat pump installations increase slightly with median income up to approximately $60,000 and then decline. In contrast, Black-majority census tracts (7.3% of tracts) show a sharp rise in use at approximately the same income level. Hispanic and no-majority census tracts have installed fewer heat pumps compared to their white counterparts across all income levels. Similarly, for white-majority and Black-majority census tracts, heat pump installations generally decrease as the percentage of rented households increases, while other racial majority census tracts have lower overall access and show flatter trends (see also Section 10 of the Supplementary Information).
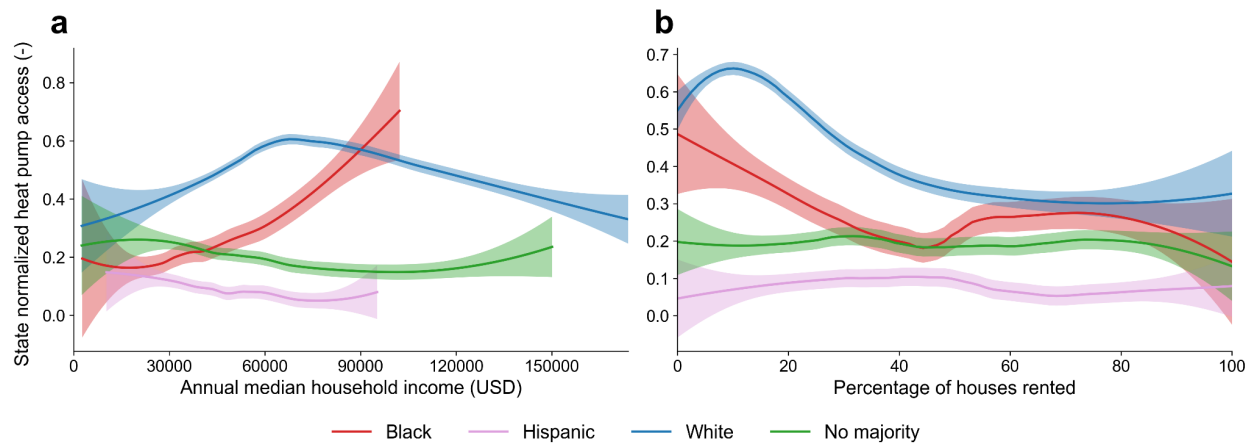

Figure 4. Nonlinear relationships between heat pump access, income, and renter status across racial/ethnic groups. Relationship between (a) median annual household income (b) percentage of houses rented and state-normalized heat pump installations by racial and ethnic majority census tract. Lines show LOESS curves and shaded regions show 90% confidence intervals (see Methods for further details).

5. Regional analysis of heat pump inequities

To assess inequities in heat pump access nationwide, we examine patterns in areas where heat pumps are highly likely to provide net household benefits (or net costs) in the form of changes to energy bills. First, we calculate the effects of heat pump access on energy bills across the U.S. by comparing heat pump operating costs to the primary heating technology (at the county level) as a function of fuel price, device efficiency, and hourly climate data (see Methods). We perform a Monte Carlo simulation to identify counties that exhibit either net benefits or net costs in 90% of simulations as well as a neutral region where at least 10% of simulations yield net benefits and at least 10% yield net costs. Note that because we focus on the equity implications of heat pump access, rather than new adoption, up front installation costs are not included. Net benefits vary across the U.S., with 53% of households seeing net benefits in terms of reduced energy bills, 19% of households seeing net costs, and 28% of households seeing no clear benefits or costs (see Figure 5a). Primary heating fuel is a key driver of benefits; in regions where electricity or fuels other than natural gas are the primary fuel, net benefits are higher (see Figure 5b). However, climate and energy prices also play an important role.

To examine inequities in heat pump use, we then run separate logistic regressions on heat pump access for each of the three cost/benefit regions calculated above (see Figure 5c-e). Using the framework presented in Section 2, a significantly negative correlation between underrepresented communities and heat pump access in the net benefits region is indicative of an inequity, as is a significant positive correlation in the net costs region. We use the same independent variables in these regressions as in our national analysis, but we focus our discussion on results related to race, income, and renter status (see Section 5 of the Supplementary Information for full results). Race and ethnicity significantly predict lower heat pump access across all three regions. However, the negative relationship between minority populations and heat pump access is larger when heat pumps provide household net benefits relative to regions with net costs. For example, a 10% increase in the Black population in a census tract leads to a 13% decrease in the odds of heat pump access in regions with net benefits, compared to a 5.4% decrease in regions with net costs. For the neutral region, we observe a larger decrease (25.8%); however, the overall effect across racial/ethnic minorities is less pronounced in comparison to regions with net benefits.
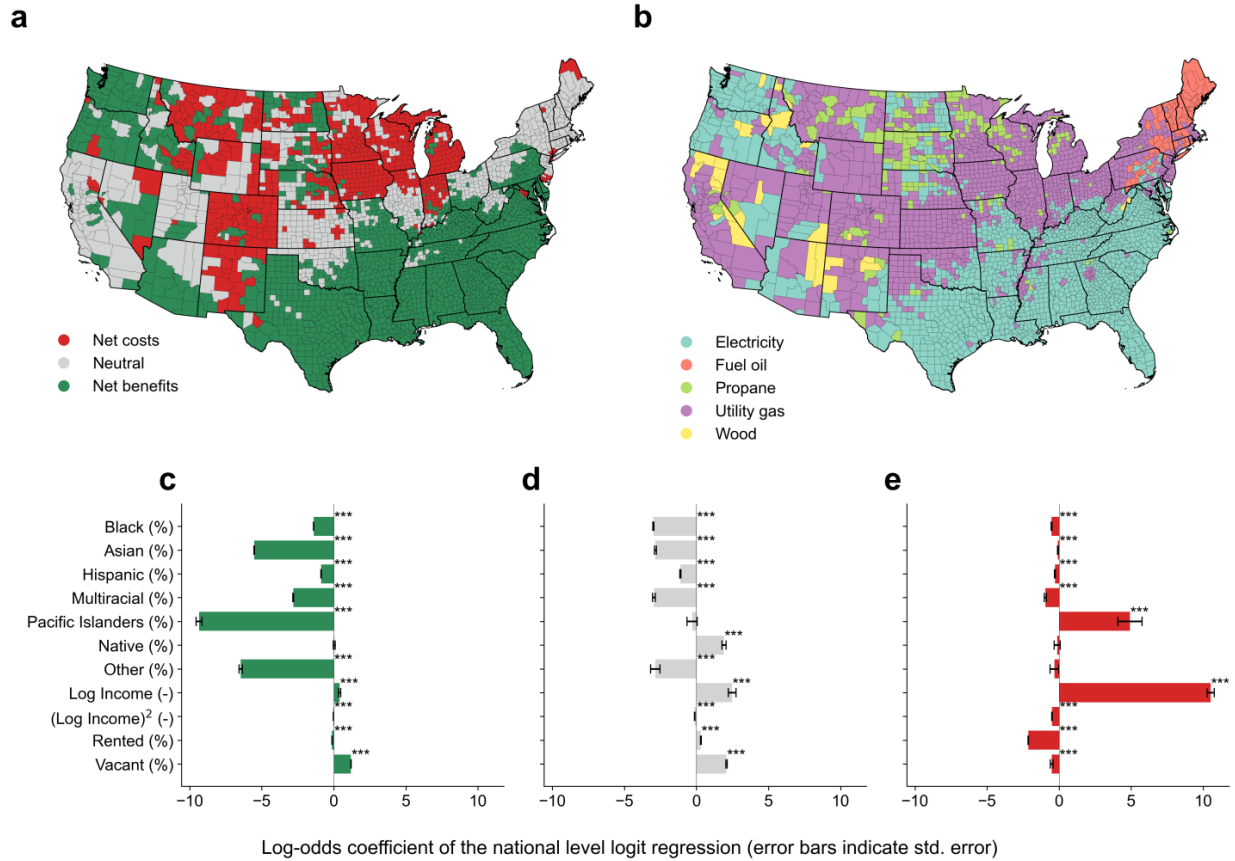
Figure 5. *Inequities in heat pump access across the U.S. (a) Regions where heat pump access is a net benefit, neutral, or net cost for households in the form of reduced energy bills and (b) primary heating source at the county level. Log odds coefficients for logistic regression results for regions where heat pumps are a (c) net benefit, (d) neutral, and (e) net cost. Symbols indicate: *** p<0.01, ** p<0.05, * p<0.1. No symbol indicates p>0.1.*

We also observe differences in the relationship between income and renter status and heat pump access across the three cost/benefit regions. To explore these differences further and assess potential nonlinearities, we repeat the LOESS analysis described in Section 4 for each of the three cost/benefit regions (see Figure S2 in the Section 10 of the Supplementary Information). We observe a generally positive relationship between income and heat pump access across all three regions up to a median income of approximately $100,000 (for net benefit regions), $65,000 (for neutral regions), and $77,000 (for net cost regions). After these levels, the effect of income is negative but smaller for the net benefit and neutral regions and larger for the net cost regions. Renter status negatively predicts heat pump access in the net benefits and net costs regions but has the largest coefficient in the latter, whereas it exhibits a very small positive relationship in the neutral region. As in the results on race and ethnicity, these results also suggest that low-income communities and communities with renters are less likely to have access to heat pumps, even in regions where they provide direct benefits, again suggesting an equity issue that will be important to address in electrification policies.

6. Discussion

Household electrification is an emerging energy justice issue in the U.S. At the national scale and across regions, we find that higher percentages of racial and ethnic minority households, lower median income, and higher percentages of renters at the census tract level all predict lower heat pump access. The negative correlations between racial and ethnic minority populations and heat pump access are largest in areas where heat pumps provide net benefits to households. While directionally the same, the negative correlation between renter status and heat pump access is largest in areas where heat pumps are likely to provide a net cost to households. Income effects are nonlinear but suggest that moderate income is generally associated with higher heat pump access across net cost and benefit regions. Taken together, these results suggest that minority communities are disproportionately excluded from the benefits of heat pumps. Additionally, our nonparametric analysis shows that higher income among Black-majority census tracts is associated with a higher likelihood of heat pump access relative to other groups, suggesting distinct relationships between heat pump access, race/ethnicity, and income.

Our analysis contributes new insight to the field of energy justice by assessing inequities in a technology that may have higher or lower operational costs than incumbents. Widely studied technologies such as rooftop solar or energy efficiency, in contrast, may have high up front costs but generally have lower operational costs across the board. By separately analyzing dynamics in regions where heat pumps have positive, negative, or neutral effects on energy bills, we can provide a more nuanced assessment of whether lower (or higher) access rates in underserved communities suggest potential inequities. Because we find evidence of racial/ethnic, income, and (to a lesser extent) renter status inequities in regions where heat pumps provide bill savings, policies, markets, or other drivers may be unjustly excluding these groups.[24,41,49,50] Conversely, lower heat pump access in regions where heat pumps raise energy bills does not represent an inequity and can help drive down costs, particularly for heat pumps designed to operate in cold climates (where they may not currently provide a net benefit). Notably, race and ethnicity are strongest negative predictors of access in regions where heat pumps are expected to result in energy bill savings, leading us to conclude that an inequity exists.

To the best of our knowledge, this study contributes the first quantitative assessment of national patterns in heat pump access. While we find robust evidence of inequalities and inequities in access for racial/ethnic minorities, low-income households, and renters, there are several areas where future research could build on these results. Because we cannot measure demographic variables at the household level, our results may under- or overestimate inequities (a common limitation in energy equity studies, particularly those at the national scale). Nevertheless, robustness checks and prior literature (which shows that environmental inequities often increase with data granularity) provide further evidence for the inequities we observe.[47,48] Future research may take advantage of more granular data to assess these dynamics at the household level. Furthermore, we focus here on access to heat pumps but do not measure patterns in adoption of new heat pumps. The demographics of new adopters may be different from those who currently have heat pumps. Because renters do not adopt new heating technologies, policies will need to target landlords who may live in a different location than the rental unit. Future work

could also explore these factors and investigate patterns of technology diffusion over time, building on advances in assessing rooftop solar.[57]

The framework we present can also be applied to other technologies whose net household benefits may be positive or negative. Additionally, while we focus on the effects of heat pump access on energy bills, clean energy technologies have a variety of costs and benefits. For example, heat pumps may have benefits such as increasing cost reliability (particularly in regions where fuel prices are highly variable, as seen with natural gas in Europe[51]) and improving thermal comfort. However, they may also have other costs such as increased vulnerability to electricity service interruptions. They may also have costs and benefits to society beyond climate change mitigation (for example, by reducing or increasing air pollution, depending on their electricity source). As more households electrify, the dynamics of these costs and benefits can change, and systems factors may create larger injustices. For example, as the customer base for natural gas utilities shrinks, the burden of cost-recovery for durable infrastructure is placed on a smaller number of remaining customers and may raise energy bills.[52–54] Underserved communities could disproportionately bear these stranded asset costs. Additionally, widespread electrification of heating may stress the electricity system.[55]

Addressing inequities in heat pump access is particularly critical in the U.S. given the passage of the Inflation Reduction Act (IRA), which allocates $43 billion in consumer incentives over ten years for energy efficiency and electrification.[56] Our analysis suggests that care will need to be taken to ensure IRA directly benefits underserved communities. While a detailed policy assessment is beyond the scope of this analysis, our findings support the need for context-specific electrification policies. For example, for locations where the heat pumps reduce energy bills, targeted outreach could be coupled with pilot programs with free or low-cost installations.[21] Clean energy technologies such as rooftop solar have been shown to follow a seeding pattern,[57] and thus these policies could encourage future adoption. It is also critical that these pilots provide cost savings,[58] both to avoid increasing energy poverty and prevent community backlash, as has been observed with time of use pricing programs.[59,60] Other policy mechanisms such as lump-sum transfers and on-bill incentives can also help ensure that low-income households benefit from these programs. By using insights on current patterns in heat pump access and their costs and benefits, policies can be designed to reduce inequities, and ultimately injustices, in electrification transitions.

6. Methods

6.1 Data sources

We analyze spatial patterns in heat pump access across the U.S. using household-level property data from the Zillow Transaction and Assessment Database (ZTRAX), accessed January 2021.[61] The dataset includes 63.7 million of these properties report heating and cooling technologies, with 38 categories (heat pumps, furnaces, boilers, radiators, space heaters, central A/C units, window A/C units, etc.). ZTRAX provides information on a variety of property characteristics including building type (multifamily, single family, trailer home, etc.), location, and

market and assessed value. Additional characteristics including number of stories, number of rooms, number of units, building area code, building area square feet, occupancy status, effective year built, and value certification date were also extracted but were excluded from the analysis as over 15% of the data in these variables were missing. For residences that did not have data on home value, assessed value was used as a substitute. The ZTRAX database includes hundreds of additional variables including home sale features and information on architecture and finishes that were deemed less relevant to this analysis. See Section 3 of the Supplementary Information for a full description of variables included in our analysis.

We then added census tract data (racial and ethnic identity, median income, homeownership status, and house age) from the American Community Survey (ACS) 5-year estimates for 2016–2020[62] via the R tidycensus package version 1.2.3.[63] The ACS data was then merged into the ZTRAX data using the household 2020 census identifiers (GEOIDs) calculated using latitude and longitude. This merge resulted in a data loss of 0.1% of ZTRAX records due to invalid location data. We also included heating and cooling degree days (HDD and CDD) calculated from average daily outdoor temperature data from the nearest NOAA weather station between 1991-2020[64] (number of days with an average temperature above or below the standard 65°F[14] outdoor temperature benchmark). We obtained natural gas utility boundaries from the Homeland Infrastructure Foundation-Level Database (HIFLD)[65] and price data (for 2020) from the EIA-176[66] form. Average prices for residential electricity customers at the utility level were extracted from the EIA Form 861.[67] Prices were normalized to 2020 using the EIA national electricity price index.[68] To calculate prices by county, we weighted the electricity price for each utility by the number of customers served. After data cleaning and merging, our final dataset includes 99.7% of all residences in ZTRAX that report heating type.

6.2 Parametric analysis

We used a logistic regression (logit) model to assess how the log odds of a residence having a heat pump relates to the racial and ethnic makeup, median income, and percentage of renters in that census tract as well as other control variables at the house, census tract, and county scale. Logit models are used to identify the probability of an event, such as having a heat pump, and are commonly used in research on household access to energy-efficient and clean energy technologies.[69] The general logit model takes the form:

$$P(H) = \frac{1}{1+e^{-Y}},$$

(1)

where $P(H)$ is the probability of heat pump installation at the household level and e is the euler's number. Y a linear function of predictors as follows:

$$Y = \beta_0 + \sum_{i=1}^{N} \beta_i R_i + \sum_{j=1}^{M} \beta_j C_j + \varepsilon,$$

(2)

where β_0 is the intercept, β_i are coefficients for equity-related variables R_i, β_j are coefficients for control variables R_j, and ε is the error term. We present results in terms of percentage change in odds and log odds (see Table 2 and Section 4 in the Supplementary Information).

The equity related variables R_i include: the fraction of households of each racial/ethnic identity (with white omitted due to collinearity), median income (log transformed), median income (log transformed) squared, and the percentage of homes that are rented and vacant (with owned homes omitted due to collinearity) at the census tract level. Racial/ethnic identity categories include (1) Black, (2) Asian, (3) Hispanic, (4) Multiracial, (5) Pacific Islander, (6) Native Hawaiian or Other Pacific Islander, (7) American Indian or Alaska Native, and (8) other (i.e., households identifying themselves as a race or ethnicity different from the categories as mentioned above). The control variables C_j include housing price and building at (at the household level); tract-level data on fuel and electricity costs, fuel availability; and state fixed effects. See Section 3 of the Supplementary information for more details on these variables. The logit models are implemented in STATA version 17. We also developed additional models (see Section 9 of the Supplementary Information) including interaction effects between race/ethnicity, income, renter status, and building age.

6.3 Nonparametric Analysis

We used nonparametric local smoothing models to illustrate how heat pump access varies across median income and homeownership status for census tracts with different racial/ethnic majorities. We used LOESS (locally weighted least squares) regression to fit local linear relationships between state-normalized heat pump access and (a) median household income, (b) the percentage of houses occupied by renters, and (c) building age (at the household level) for census tracts with majority populations of different racial and ethnic groups. We only include racial and ethnic groups that have a majority in at least one percent of the total census tracts which leads to the exclusion of all the other races/ethnicities besides white, Black, and Hispanic (see Figure S2 in Section 10 of the Supplementary Information). Because LOESS smoothing does not require a global function to fit all data, it allows us to observe the otherwise difficult-to-interpret non-linear relationships between income or homeownership and heat pump access.[17] LOESS was implemented using the R stats package version 4.2.1.[70] For better visualization, outliers were removed by limiting the annual median income to the bottom 98 percentile for each racial/ethnic category.

Localized effects such as heating and cooling demand, electricity prices, and incentives for heat pump adoption (and thus access) are partially mitigated in our nonparametric analysis by calculating the state-normalized heat pump access (S_i), which normalizes census-tract-level heat pump access by the population *(P)* weighted heat pump access in each state:

$$S_i \;=\; HP_i \,/\, \sum_{i=1}^{T}\left(\frac{P_i}{P_s} * HP_i\right),\ \ i = 1,...,N\ , \tag{2}$$

where HP_i is the heat pump access percentage in census tract i, s is the state, and T are the total number of census tracts in the state. A value greater than one indicates that the census tract has installed more heat pumps compared to the state average (and vice versa). We applied this method to calculate separate nonparametric curves for census tracts based on their racial/ethnic majority. For example, if more than 50% of the population of a census tract self-identified as Black, the census tract was designated as a Black majority tract. We also included census tracts with no racial/ethnic majority, meaning that no one group represented at least 50% of the population.

6.4 Robustness checks

Our findings are limited by several features of the available data. For example, ZTRAX under-reports heat pump presence in households, with 10.5% of households that report heating type in ZTRAX reporting that they have a heat pump compared to an estimated 15.3% of U.S. households from the 2020 Residential Energy Consumption Survey (RECS).[71] Some of these differences are likely due to different reporting practices for heating and cooling types between RECS and individual town/county tax assessor databases (where ZTRAX sources its data). Additionally, because our sociodemographic data is at the census tract level, we do not know the racial identity of households with high heat pump access, only the tract-level percentage of racial and ethnic identities (as well as income, renter status, etc.). It may be the case, for example, that racial/ethnic minority households within census tracts with higher white populations are responsible for the higher observed odds of heat pump access within those tracts, but these dynamics would not be visible in our data. This lack of household-level sociodemographic data granularity is a common feature of studies of energy and environmental justice and can lead to results that under- or over-estimate inequities.

To address this challenge, we replicated our parametric analysis using data from RECS.[71] RECS is a periodic study conducted by the U.S. Energy Information Administration (EIA) that includes household-level survey data on geography, climate, income, household quality, and renter/owner status. The RECS sample is designed to meet precision requirements on energy consumption for all 50 states and Washington, DC, with a total of 18,496 respondents.[72] We use this data to assess how the use of heat pumps as the main heating equipment correlates with equity (racial and ethnic makeup, income, and renter status) and other control variables at the household level. The logit model is implemented in R using the survey package[73], which is recommended by EIA to capture the sampling weights used in the RECS survey methodology.[74] The results of this robustness check are qualitatively similar to the results of our main analysis (see Section 6 of the Supplementary Information). We also conduct robustness checks using different model specifications (see Section 9 of the Supplementary Information).

6.5 Net benefits analysis

We estimate the net benefits of switching to a heat pump from the current heating technology in terms of the expected change in household operational costs (i.e., energy bills). Our analysis uses inputs on the primary heating technology (from the ACS 2016-2020 survey) and average annual electricity prices at the county level. Additionally, we use state-level data on natural gas,

propane, fuel oil, and wood prices. All prices are from 2020. We calculate the coefficient of performance (COP) of a heat pump in each county using hourly temperature profiles from typical meteorological year data.[75] We use a function that assumes a linear relationship between temperature and COP for temperatures between 5 and 47°F for heat pumps of similar capacity (25,000 BTU) based on the Northeast Energy Efficiency Program (NEEP) (see Section 7.3 of the Supplementary Information). This function has been used in previous studies.[13,14] We assume average efficiencies of 80% for natural gas and propane furnaces, and 83% fuel oil furnaces (based on the 2015 Federal standard for residential furnaces[76]), and 79% for wood stoves (based on the average efficiency reported by the EPA-certified wood stove database).[77]

Using these inputs, we calculate the energy bill (electricity and fuel) savings or costs for a typical[27] single-family, detached house:

$$s = \sum_{i=1}^{8760} \frac{Pc \cdot q_i}{\eta_c} - \frac{Pe \cdot q_i}{COP(T_i)}$$

where s are the net energy bill savings (or, if negative, costs), Pc and Pe are the prices of current heating fuel and electricity, q_i is the hourly heating load, η_c is the efficiency of the current heating device (e.g., natural gas furnace), and $COP(T_i)$ is the heat pump efficiency, which depends on outside temperature at hour i. While the absolute costs can depend strongly on heating load, which is a function of house characteristics (e.g., level of insulation, age, etc.), the relative savings or costs of different heating sources are likely to be similar. While our approach does not include differences in housing characteristics, we do include a higher level of spatial granularity compared to previous studies on the costs of heat pump use.[13,14,78] For complete details on our approach, see Section 7 of the Supplementary Information.

To account uncertainties, we use a Monte Carlo simulation. For heating technology efficiencies, we construct triangular distributions using 78% as the minimum efficiency for natural gas, propane and fuel oil furnaces (based on the 1992 Federal standard[76]) and 58% for wood stoves (the minimum value reported in the EPA-certified wood stove database[77]). For maximum values, we use 99% for natural gas and propane, 96.7% for fuel oil furnaces (based on the highest efficiency in the Energy Star certified furnaces database[79]) and 90% for wood stoves (based on the maximum efficiency in the EPA-certified wood stove database). We use a triangular distribution with a minimum and maximum COP of 3 and 5 at 47°F for the heat pump COP, based on values in the NEEP database (note that the minimum COP can be as low as 1 for air temperatures below 47°F). For the price of electricity, natural gas and other delivered fuels, we use triangular distributions based on the historical national variation (the coefficient of variation using two standard deviations and the mean of national average prices as a percentage of 2020 prices) from 2000 to 2020. See Section 7.5 of the Supplementary Information for full details on the uncertainty distributions. We run the Monte Carlo simulation 10,000 times.

Data and code availability

Individual property data were provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at

Conflict of interest

The authors declare no conflicts of interest.

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Supplementary Information

Assessing inequities in electrification via heat pumps across the U.S.

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Contents

Section 1: Heat pump technologies and costs

Heat pumps are an efficient, electric heating and cooling technology. They are generally substantially more efficient than other sources of heating and cooling and can be a lower-emissions alternative to traditional heating systems, particularly when powered by electricity from low-carbon sources.[1,2] While traditional furnaces are powered by the combustion of fossil fuels like natural gas, propane, and heating oil (and traditional electric heaters use electric resistance to provide heat), heat pumps use electricity to transfer heat from one location to another. The underlying operation of a heat pump is based on using mechanical work (i.e., a compressor unit) to increase the pressure (and thus, the temperature) of a refrigerant fluid and circulate it through a heat exchanger inside a building to provide space heating.[3] Typically, heat pumps can also be used for indoor space cooling by reversing the direction of the refrigerant fluid, which draws heat from indoors and expels it to the ambient environment. The ability of heat pumps to provide both heating and cooling is a key advantage over traditional heating and cooling systems that rely on two separate devices (e.g., a furnace and an air conditioner) and can be particularly beneficial for homes that do not already have air conditioning systems.

Three types of heat pumps are currently available on the market: air-, ground-, and water-source. Air-source heat pumps (ASHPs), which transfer heat between indoor and outdoor air, are the most common type used in the U.S[2] and have a global market share of over 60%. ASHPs may be connected by ducts but are also available as ductless devices (i.e., mini-split) for homes without ducts. While there is heat in outdoor air even in winter, ASHPs become markedly less efficient in extremely cold climates.[4] Traditionally, dual fuel systems are used in these cases, where a gas furnace or electric resistance heating system provides backup heat. However, improvements in two-stage heat pump systems, which have an additional compression cycle, can reduce the need for backup heating in colder regions and maintain comfort on colder days.[5] Ground-source heat pumps (GSHPs), which transfer heat between indoor space and the nearby ground, can also operate more efficiently in colder climates but are less common due to their higher capital costs and specific technical skills required for

installation.[6] Water source heat pumps use submerged pipes to transfer heat to and from a water source and are thus limited to areas with an appropriate source.

The costs of heat pumps vary significantly across households.[7] For ASHPs, typical installation costs in the U.S. range from 4,000 to 12,000 USD, with an average of about 8,000 USD.[8] Home size and efficiency and local climate can lead to different sizing specifications for heat pumps and thus equipment costs. Costs of labor can also vary across locations. As demand for heat pumps increases with policy support and market incentives (and high natural gas prices driven by geopolitical events), the costs of heat pumps may also rise temporarily as value chains adjust, particularly in locations with fewer trained installers.[9] Large regional differences in operating costs of heat pumps are common and depend on local climate and the costs of electricity compared to natural gas and other fuels.[10] This large variation in costs is a key motivation for the framework we propose that uses net household benefits in assessing inequalities, inequities, and injustices in heat pump use across the U.S.

Several factors are likely to change the net public and private benefits of heat pump use in the future. Technological improvements will allow heat pumps to operate more efficiently (requiring less electricity to provide the same heating output), particularly in colder climates where efficiency poses the greatest barriers. New business models that lower installation costs and provide greater operational flexibility could also increase the value of heat pumps for users and electric utilities.[11] Furthermore, net benefits could change if the price of natural gas and other fuels rise or fall relative to the price of electricity. From a climate perspective, studies suggest that heat pump use rates of up to 90% can cost-effectively reduce greenhouse gas emissions in the U.S. by 2050.[12] However, potential cost setbacks could also occur, including reductions in fossil fuel prices with reduced demand and as well as challenges for electric grid operations with large-scale use.[13] Nevertheless, taken together, research suggests that future decarbonization of electricity and heat pump cost declines due to technological improvements can further increase the public and private benefits of heat pump use across the U.S.

Section 2: Heat pump policies and incentives

There is a strong rationale for public policy to support heat pump adoption. The net public benefits (including health and environmental benefits) of heat pumps are positive in many parts of the U.S., but the private costs to households may be greater than fossil fuel alternatives (particularly natural gas).[14] Even in locations where heat pumps have lower life cycle costs, high up-front costs can impede adoption,[15] a challenge that is further exacerbated by credit and liquidity constraints for some households.[16] These costs may include the heat pump itself as well as electrical panel and other home upgrades that may be required.[17] Cost barriers may be especially acute in emergency installation cases, where the current heating system has failed and there may be limited time to upgrade home systems to be heat pump ready. Furthermore, in some areas, the operating costs of heat pumps exceed those of natural gas furnaces. This feature makes heat pumps different from many other household technologies such as energy efficiency or rooftop solar, where operating costs are relatively low or zero.

Policies to incentivize energy efficiency and clean energy technologies typically aim to improve access to capital, reduce the burden of high upfront costs, lower financing costs, and address split incentives.[23] At the federal level, schemes like the Weatherization Assistance Program (WAP) install energy efficiency upgrades for low-income residents, such as insulation, furnace repair or replacement, duct sealing, and refrigerator replacements.[24] State and local governments may also provide tax incentives, direct rebates, or grants. Additionally, in most states, utility regulatory commissions mandate utilities to use ratepayer dollars to fund low-income energy efficiency programs,[25] and utilities may also provide incentives through mechanisms such as on-bill financing. These approaches have also been used by various states to incentivize rooftop solar, including on-bill financing for solar installations and no-cost installation for low-income households.[26] These policies and programs continue to serve an important role in motivating residential energy efficiency and clean energy access. However, new policy mechanisms will also be important; for example, policies targeting increased adoption by landlords will be important to improving access for renters.

For heat pumps specifically, rebates and loans are the two most widely available incentives.[27] Heat pumps may be eligible for various federal, state, local, and utility energy efficiency incentives or promoted through targeted programs. The recently-passed Inflation Reduction Act (IRA) substantially expanded incentive programs to provide up to $14,000 USD in direct consumer rebates for families to buy heat pumps and other energy-efficient home appliances.[28] At the state level, Northeastern states such as Maine, Vermont, and Massachusetts also provide direct support for heat pumps. Policies differ by state, but most take the form of rebates for either customers (down-stream) or installers (up or mid-stream). The rebate amount is generally determined by household annual income, size of the heat pump, fuel type, and/or duct status. For example, Vermont offers additional rebates for people below a certain income, while New Hampshire offers whole-house incentives to offset greater portions of energy use.[29] Such policies seek not only to incentivize the adoption of energy-efficient technologies like heat pumps but also to bring down household energy bills and invest in energy justice.

Section 3: Description of variables

This section describes the equity and control variables included in the analysis, including their theoretical basis, data sources, and interpretation (see Table 1 for descriptive statistics).

3.1 Median Income

Income can predict household access to energy-efficient and clean energy technologies, many of which have high up-front costs. Following previous work, we use the logged median annual household income at the census tract level using table S1901 of the five-year estimates from the American Community Survey (ACS) for 2016-2020.[30–33] To further account for tail effects at the far upper and lower ends of income, we also include the square of logged income.

3.2 Tenancy Status

Homes are less likely to have energy-efficient and clean energy technologies if they are renter and not owner occupied, due to the split-incentive problem between landlords and tenants.[31] We

extract data from ACS table B25002, which classifies every housing unit as either vacant or occupied, and ACS table B25008, which divides the occupied housing units into renter-occupied and owner-occupied categories.[32] Combining both the tables, we establish the percentage of homes that are vacant, owner-occupied, or renter-occupied in each census tract. These variables are used to estimate the impact of homeownership on heat pump access.

3.3 Race/ethnicity

Race and ethnicity can predict access to energy-efficient and clean energy technologies, even after controlling for income and tenancy status, indicating possible systematic racial/ethnic barriers to access to these technologies. We use categories for race/ethnicity defined in ACS table B03002, which include: White, Black, Hispanic, Asian, Pacific Islander, Native, "Two-or-more," and "Other".[32] The Hispanic category refers to those identifying as only Hispanic or Latino or Hispanic or Latino along with another race category. These values are divided by the total population in each census tract to calculate the percent of the population that identifies as different racial/ethnic groups. We use white as the baseline category.

3.4 Building Age

Newer buildings are more likely to use electricity for space heating, whereas older buildings are more likely to heat with natural gas, oil, propane, or wood.[34] We include both the census-tract-level building age from the five-year estimates from the ACS[32] and the individual year of construction or last code-triggering renovation for each unit included in the ZTRAX database. The primary analysis utilizes the latter to develop a continuous building age variable. We also use building age for ACS as a robustness check. ACS reports building age in decade groupings and coded as dummy variables: pre-1940 construction, 1940-49, 1950-59, 1960-69, 1970-79, 1980-89, 1990-99, 2000-10, and post-2010.[35] We use new construction (post-2010) as the baseline because installing heat pumps in new buildings is widely seen as easier and less expensive compared to retrofits in older buildings.[36]

3.5 Electricity prices

Higher electricity prices increase the costs of operating a heat pump as well as an electric resistance heater. We use electricity price data from the EIA form 861, which reports average prices per kWh for residential customers at the utility-county level, for the years 2016 through 2021.[37] Total revenue from residential sales by utility-county were divided by total kWh sales by utility-county to assess average price for each year. Three Texas utilities also did not report prices during the period of the analysis (Oncor, CenterPoint and Texas-New Mexico). For homes serviced by these utilities, we use average county data from their FERC form 1 reports (page 300).[38] We also cleaned the data by reassigning county names or boundaries that had changed since the time of the last report (namely in Alaska).

Prices were then normalized to 2020 prices using the EIA national electricity price index. To identify county-level prices for counties serviced by more than one utility, we calculated a customer-weighted average electricity price. Electricity prices were subsequently standardized by mean centering and dividing by their standard deviation.

3.6 Natural gas prices and access

Low natural gas prices make switching to a heat pump comparatively less advantageous. Prior research shows that operational cost is a significant predictor of households decisions to install a heat pump, with natural gas price (and access, as 17% of homes do not have gas access) predicting lower heat pump adoption and therefore access.[12] First, we map each household in ZTRAX (latitude and longitude) onto the publicly available natural gas service territories from Homeland Infrastructure Foundation-Level Data (HIFLD).[39] Second, obtain natural gas prices for each utility boundary from the EIA-176 forms for 2016 (in USD per thousand cubic foot).[40]

Approximately 16% of territories were not matched to a record in the EIA-176 form. We used fuzzy string matching to match additional utility territories to pricing data. We matched approximately 7% of utility boundaries with strict criteria, which left approximately 9% of utilities unmatched. For the remaining utilities, we used state average prices reported from EIA[40] for 2020. We use standardized prices in our logistic regression models. In addition, we included a binomial utility gas access variable which was defined as 1 if the household was served by a natural gas utility service company and 0 otherwise and used this variable in place of gas prices as a robustness check on our model (see Section 9).

3.7 Climate

Heat pumps are less efficient in cold climates, and thus less likely to be cost effective.[41] Additionally, they may be less likely to be present in areas with minimal heating needs, where the benefits of their increased efficiency relative to electric resistance heating are less impactful compared to the higher upfront cost. We include heating and cooling degree days (HDD and CDD) in our model to control for heating and cooling requirements. For cooling degree days, the value reflects the number of days the average outside air temperature of a given location was above 65°F (the standard temperature used in the U.S. to maintain indoor comfort) multiplied by the difference between 65°F and the average daily temperature. For heating degree days, the value reflects the inverse (i.e., days with average temperature below 65°F, when heating is needed to maintain comfort). Annual HDD and CDD values with a standard reference of 65°F were obtained from the National Oceanic and Atmospheric (NOAA) 1991-2020 weather normals for 7300 weather stations nationwide.[42] We then matched each household to the nearest weather station and assigned the recorded HDD and CDD values.

3.8 State fixed effects

We expect some local fixed effects on heat pump access given differences in the policies, histories, geographies, markets, and trends of individual states. To control for these effects, we include state-level fixed effects in our parametric analysis. Owing to reporting differences between jurisdictions, several states also reported zero heat pumps within their service territory and were excluded from the analysis. These states include Hawaii, Louisiana, New Jersey, New York, and Vermont. Alaska was used as the reference state.

3.9 Housing type

To control for differences in household type, we use dummy variables for housing type designations in the ZTRAX database. We use five different housing types in our analysis: 1) Single-family, 2) Single-family shared wall, 3) Multi-family, 4) Trailer/Mobile home, and 5) Other. Multi-family was used as the reference category.

3.10 Descriptive statistics for variables

Table 1. *Descriptive statistics for variables used in our parametric analysis to assess spatial patterns in heat pump access across the U.S.*

Variable	Mean	Standard Deviation	Unit
Home Value	330,041	2,153,357	$ house price
Electricity price	0.13	0.04	$/kWh
Natural gas price	11.94	3.62	$/thousand ft3
Gas Access (%)	0.84	0.35	% with access
Heating degree-days	3,951	2,093	°F-degree days/year
Cooling degree-days	1,553	1,022	°F-degree days/year
Median Income	70,123	34,813	$ annual income
Building age	46.54	22.21	years
Owned (%)	62.54	22.37	% homes
Rented (%)	32.18	21.56	% homes
Vacant (%)	5.28	6.78	% homes
White (%)	62.25	28.99	% individuals
Black (%)	12.79	20.33	% individuals
Asian (%)	4.67	8.51	% individuals
Hispanic (%)	14.36	19.33	% individuals
Multiracial (%)	4.91	4.61	% individuals
Pacific Islanders (%)	0.13	0.75	% individuals
Native (%)	0.60	3.11	% individuals
Other (%)	0.29	1.10	% individuals
Multifamily Building Type (%)	4.26	10.40	% buildings
Other Building Type (%)	1.14	6.01	% buildings
Single Family Building Type (%)	82.27	23.50	% buildings
Single Family Shared Wall Building Type (%)	12.31	20.51	% buildings
Trailer Home Building Type (%)	0.02	0.61	% buildings

Section 4: National regression results

Table 2. Coefficient estimates and standard errors for the national logistic regression model for heat pump access. State and housing type (extracted from ZTRAX) dummy variables are also included in the model but not shown here for brevity. The percentage change in odds for a unit change in log income was calculated with a value of $70,123 (average of census-tract median income values in the dataset). The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless.

Variable	Log Odds Coefficient	S.E.	Unit Change	Odds Change (%)
Black (%)	-1.442***	0.005	0.1	-13.429
Asian (%)	-4.308***	0.017	0.1	-35.001
Hispanic (%)	-0.906***	0.01	0.1	-8.662
Multiracial (%)	-2.801***	0.025	0.1	-24.429
Pacific Islanders (%)	-8.156***	0.174	0.1	-55.763
Native (%)	1.295***	0.047	0.1	13.826
Other (%)	-5.779***	0.098	0.1	-43.892
Log Income (-)	3.595***	0.072	Log(1.1)	-4.711
(Log Income)^2 (-)	-0.183***	0.003	-	-
Rented (%)	-0.428***	0.007	0.1	-4.19
Vacant (%)	0.961***	0.011	0.1	10.087
Log Home value (-)	0.016***	0.001	1	1.633
Building age (-)	-0.741***	0.001	1	-52.336
Heating degree-days (-)	-0.523***	0.005	1	-40.726
Cooling degree-days (-)	-0.172***	0.005	1	-15.802
Electricity price (-)	0.217***	0.002	1	24.234
Natural gas price (-)	-0.022***	0.001	1	-2.166
State dummies	Yes	-	-	-
Housing type dummies	Yes	-	-	-
Constant	-22.69***	0.407	-	-
Pseudo R^2	0.3333	-	-	-
Observations	51,139,213	-	-	-

Section 5: Regional regression results

Table 3. Coefficient estimates and standard errors for the regional logistic regression models for heat pump access, where regions are defined based on household benefits (in the form of reduced energy bills). State and housing type (extracted from ZTRAX) dummy variables are also included in the model but not shown here for brevity. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless.

Variable	Net benefits		Neutral		Net costs	
	Log Odds	S.E.	Log Odds	S.E.	Log Odds	S.E.
Black (%)	-1.401***	0.005	-2.982***	0.037	-0.523***	0.026
Asian (%)	-5.519***	0.022	-2.851***	0.064	-0.082***	0.028
Hispanic (%)	-0.879***	0.011	-1.119***	0.035	-0.288***	0.029
Multiracial (%)	-2.819***	0.027	-2.948***	0.090	-0.951***	0.075
Pacific Islanders (%)	-9.355***	0.202	-0.298	0.355	4.920***	0.846
Native (%)	0.029	0.061	1.913***	0.138	-0.128	0.217
Other (%)	-6.462***	0.112	-2.857***	0.326	-0.321	0.300
Log Income (-)	0.396***	0.080	2.471***	0.269	10.52***	0.256
(Log Income)^2 (-)	-0.032***	0.004	-0.122***	0.012	-0.492***	0.011
Rented (%)	-0.131***	0.007	0.307***	0.023	-2.133***	0.022
Vacant (%)	1.192***	0.012	2.085***	0.043	-0.511***	0.090
Log Home value (-)	-0.026***	0.001	0.161***	0.002	0.076***	0.002
Building age (-)	-0.822***	0.001	-0.601***	0.004	-0.162***	0.003
Heating degree-days (-)	-0.215***	0.006	0.188***	0.019	-1.569***	0.030
Cooling degree-days (-)	0.066***	0.005	0.751***	0.018	-1.795***	0.028
Electricity price (-)	0.360***	0.003	-0.012*	0.008	-0.937***	0.012
Natural gas price (-)	-0.079***	0.002	0.010	0.008	-0.168***	0.009
State dummies	Yes	-	Yes	-	Yes	-
Housing type dummies	Yes	-	Yes	-	Yes	-
Constant	-6.626***	0.448	-22.15***	1.514	-61.29***	1.493
Pseudo R^2	0.3189	-	0.1953	-	0.2642	-
Observations	27,216,988	-	14,454,856	-	9,466,140	-

Table 4. Change in odds for the regional logistic regression models for heat pump access, where regions are defined based on the household costs or benefits (in the form of energy bill changes). State and housing type (extracted from ZTRAX) dummy variables are also included in the model but not shown here for brevity. The percentage change in odds for a unit change in log income was calculated with a value of $70,123 (average of census-tract median income values in the dataset). The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless. For the significance and standard error of each variable, see Table 2.

Variable	Net benefits	Neutral	Net costs
	Odds change (%)	Odds change (%)	Odds change (%)
Black (%)	-13.073	-25.785	-5.096
Asian (%)	-42.415	-24.806	-0.814
Hispanic (%)	-8.415	-10.587	-2.839
Multiracial (%)	-24.565	-25.532	-9.072
Pacific Islanders (%)	-60.761	-2.936	63.558

Native (%)	0.292	21.082	-1.272
Other (%)	-47.597	-24.851	-3.159
Log Income (-)	-2.994	-2.477	-4.712
(Log Income)^2 (-)	-	-	-
Rented (%)	-1.301	3.118	-19.209
Vacant (%)	12.660	23.183	-4.982
Log Home value (-)	-2.596	17.468	7.950
Building age (-)	-56.045	-45.174	-14.956
Heating degree-days (-)	-19.346	20.683	-79.175
Cooling degree-days (-)	6.780	111.912	-83.387
Electricity price (-)	43.333	-1.232	-60.820
Natural gas price (-)	-7.550	1.004	-15.465

Section 6: Replication results

As with many previous studies investigating the equity impacts of clean energy technology access,[31,43] our study evaluates inequities at the census tract level. However, it is possible that this approach can under- or overestimate inequities in access, if for example Black households in a location with a higher proportion of white residents are more likely to have access to heat pumps than Black households in a location with a higher proportion of Black residents. To explore this possibility, we replicate our analysis using the 2020 Residential Energy Consumption Survey (RECS).[44] RECS is a periodic survey conducted by the U.S. Energy Information Administration (EIA) that includes household-level data on variables such as geography, climate, income, household quality, race and ethnicity, and renter/owner status. The 2020 RECS sample was designed to meet precision requirements on energy consumption for all 50 states and Washington, DC, with a total of 18,496 respondents.[45] We use RECS data to assess how the use of heat pumps as the main heating equipment correlates with equity (racial and ethnic makeup, income, and renter status) and other control variables at the household level. The model is implemented in R using the survey package,[46] recommended by EIA to capture the replicate weights used in the RECS methodology.[47]

The results for the relationship between household race/ethnicity and heat pump access are generally consistent with the results from our main analysis (see Table 5). Specifically, heat pump access is significantly lower among Black or African American households than white ones, and among households of Hispanic and Latino descent than non-Hispanic/Latino households (RECS codes for Hispanic/Latino as a separate ethnicity variable). This result remains robust when controlling for the same factors included in the primary analysis: income, rental status, building type and year, climate, natural gas access, and state. The direction of the relationship for other racial categories (except American Indian or Alaska Native) is also negative, consistent with our main analysis, although it is not statistically significant. Overall, these results provide some evidence that the use disparities observed in our data analysis are robust and likely not the result of systematic biases in the ZTRAX dataset.

The following list elaborates on the variables included in the RECS analysis, their interpretability, and key differences from the ZTRAX dataset variables, if any:

1. **Race:** The racial categories in the RECS dataset are (1) White alone, (2) Black or African American alone, (3) American Indian or Alaska Native alone, (4) Asian alone, (5) Native Hawaiian or other Pacific Islander alone, and (6) multiracial. As in the main analysis, white is used as the baseline group.

2. **Ethnic Descent:** The RECS survey delineates Hispanic/Latino descent as a separate variable from race. This binary variable is added to all logit models, with 0 referring to non-Hispanic/Latino and 1 referring to Hispanic/Latino.

3. **Income:** While the median annual income (at the census tract level) in the primary analysis is a continuous variable, the RECS dataset groups income into 16 discrete ranges, from less than $5,000 to $150,000 or more. We use the smallest range (less than $5,000) as the baseline group.

4. **Building Age:** In the RECS dataset, building age is grouped into five or ten year ranges from 1950 to 2020, with an additional pre-1950 category. Similar to the main analysis, the building age range closest to the present is used as the baseline group.

5. **Housing Type:** There are five building types in the RECS dataset: (1) mobile home, (2) single-family house detached from any other house, (3) single-family house attached to one or more other houses (for example, duplex, row house, or townhome), (4) apartment in a building with 2 to 4 units, and (5) apartment in a building with 5 or more units. As in the main analysis, detached single-family house (2) is used as the baseline group.

6. **Natural Gas Access:** Instead of using natural gas prices, the closest variable available in the RECS dataset is a dummy variable on natural gas access. We use 1 to refer to a household that has natural gas available in underground pipes, and 0 otherwise.

7. **Other Variables:** The remaining variables in the RECS dataset are largely similar to our main analysis, with minor differences. Tenancy in the RECS dataset includes not just homeownership (baseline group) and renter status, but a third status of occupancy without payment of rent.

Table 5. *Coefficient estimates and standard errors of the logistic regression model using the RECs dataset. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** $p<0.01$, ** $p<0.05$, * $p<0.1$). (HH = household.) Variables labeled "-" are dimensionless.*

Variable	Log Odds Coefficient	S.E.	Unit Change	Odds (%)
Black or African American HHs	-0.259***	0.093	0.1	-2.556
American Indian or Alaska Native HHs	0.088	0.301	0.1	0.881
Asian HHs	-0.108	0.147	0.1	-1.077
Native Hawaiian or Other Pacific Islander HHs	-0.211	0.615	0.1	-2.093
2 or more Race HHs	-0.147	0.201	0.1	-1.461
Hispanic or Latino Descent HHs	-0.469***	0.106	0.1	-4.583
Annual HH Income $5,000 - $7,499	-0.172	0.288	1	-15.835
Annual HH Income $7,500 - $9,999	0.155	0.266	1	16.822

Annual HH Income $10,000 - $12,499	-0.204	0.237	1	-18.430
Annual HH Income $12,500 - $14,999	-0.330	0.263	1	-28.075
Annual HH Income $15,000 - $19,999	0.200	0.207	1	22.189
Annual HH Income $20,000 - $24,999	0.079	0.193	1	8.207
Annual HH Income $25,000 - $29,999	-0.053	0.201	1	-5.131
Annual HH Income $30,000 - $34,999	0.011	0.188	1	1.143
Annual HH Income $35,000 - $39,999	-0.046	0.200	1	-4.526
Annual HH Income $40,000 - $49,999	0.009	0.180	1	0.921
Annual HH Income $50,000 - $59,999	0.072	0.179	1	7.441
Annual HH Income $60,000 - $74,999	0.148	0.174	1	15.934
Annual HH Income $75,000 - $99,999	0.128	0.172	1	13.628
Annual HH Income $100,000 - $149,999	0.125	0.174	1	13.346
Annual HH Income $150,000 or more	0.158	0.175	1	17.155
Rented HHs	0.028	0.084	0.1	0.279
Occupied Without Payment of Rent	-0.253	0.248	0.1	-2.495
Year Built 2010 to 2015	-0.175	0.158	0.1	-1.738
Year Built 2000 to 2009	-0.345**	0.134	0.1	-3.388
Year Built 1990 to 1999	-0.244	0.136	0.1	-2.407
Year Built 1980 to 1989	-0.226	0.139	0.1	-2.237
Year Built 1970 to 1979	-0.347**	0.140	0.1	-3.414
Year Built 1960 to 1969	-0.436***	0.151	0.1	-4.265
Year Built 1950 to 1959	-0.549***	0.160	0.1	-5.342
Year Built Before 1950	-0.745***	0.156	0.1	-7.175
Heating degree-days (-)	0.000***	0.000	1	-0.041
Cooling degree-days (-)	0.000***	0.000	1	-0.015
Natural Gas Access	-1.161***	0.058	1	-68.686
Housing Type Dummies	Yes	-	-	-
State dummies	Yes	-	-	-
Constant	1.562***	0.305	-	-
Pseudo R^2	0.211	-	-	-
Observations	18496	-	-	-

Section 7: Estimation of heat pump benefits

This section describes our approach to estimating net energy bill savings from switching to a heat pump relative to the current primary heating fuel for each county in the U.S.

7.1 Data sources

We extract heating technology data from the ACS five-year survey 2016-2020.[32] Five primary fuels are used: (1) utility gas, (2) electricity, (3) bottled, tank, or liquified propane (LP) gas, (4) fuel oil or kerosene, and (5) wood. We use Typical Meteorological Year (TMY3) weather data from NOAA[48] (reported as hourly temperatures at the county level) and estimate county-level

heating degree hours using a standard reference temperature of 18.3°C (65°F), which is also used by NOAA to calculate heating and cooling degree days.[42]

We use energy prices for 2020 at the state level (for natural gas and other fuels) and at the county level (for electricity). For natural gas, we use annual state average residential prices reported by EIA (in USD per thousand cubic feet)[49] and convert them to USD/kWh using the state-average heat content of utility gas delivered to customers (in BTU per cubic foot) from EIA.[50] For other fuels, we use residential pricing data inferred by the State Data Energy System (SEDS)[51] at the state level. For fuel oil, we use the prices reported for kerosene. For bottled, tank, or LP gas, we use the prices provided for propane.

For electricity prices, EIA form 861 gathers electricity prices at the utility level across the US.[37] We use average utility prices by county as in our parametric analysis (see Methods). Electricity prices are population-weighted averages per county inferred from EIA form 861 as the ratio of utility sales (USD) and total energy sold (kWh). For our calculation of net energy bill impacts, we assume that counties that currently report electricity as the primary heating source in ACS use electric resistance heating as the main technology.

7.2 Heating load

We use the heating degree-day method to estimate the annual heating load of a typical single-family detached house.[15] This method uses local heating degree day data (at the hourly resolution) and a heat loss factor to calculate energy demand for heating. We focus our analysis on the sign (positive, negative, or neutral) of net energy cost savings of installing a heat pump in a given location, relative to the current primary heating technology in that location. Housing characteristics such as insulation and type of construction can substantially impact heating load. However, heating load affects the costs of both heat pumps and the comparison technology, and thus differences in heating load are less likely to change the sign of the net benefits of switching to a heat pump. For this reason, we use a heat loss factor UA, which is the product of the heat transfer coefficient U and the area A, for a typical house in the U.S.

We use the RECS 2015 dataset to infer an average UA factor for a single-family, detached house in the U.S.[52] We filter RECS data to include only single-family detached houses, which includes 3,752 houses. The RECS dataset includes the average total energy use for space heating (Q_{avg}, 41.69 million BTU per year) and average annual heating degree days (HDD_{avg}, 3,773°F-day, with a reference of 65°F). We calculate the UA factor as follows:

$$UA \; = \; \frac{Q_{avg}}{HDD_{avg}} = \frac{41.69e6\, BTU}{3773\, °F·day},$$

which is (with unit conversions) 0.243 kWh/hr/°C. This is 7% above the typical value for a single-family detached house in the Midwest[15] (UA = 0.226 kWh/hr/°C), since U.S. houses, on average, will have poorer insulation. We then estimate the annual heating load (Q_i) for N_c counties as follows:

$$Q_i = \sum_{j=1}^{8760} UA \cdot HDH_{i,j}, \quad i = 1, 2, ..., N_c,$$

where $HDH_{i,j}$ are the county heating degree hours, j are hours in the year, and i are counties.

7.3 Energy costs

Heat pump. The coefficient of performance (*COP*) for a heat pump can be described as a linear function of temperature (*T*). Following previous research,[53] we calculate the parameters in this function using a range of heat pumps with a capacity of approximately 25,000 BTU/hr from a database compiled by the Northeast Energy Efficiency Partnership (NEEP).[54] (While the database has been updated, these updates do not change the coefficients substantially.) The COP is expressed as a function of outside air temperature (*T* in °F) for all counties as follows:

$$COP(T) = 0.05 \cdot T + 1.6, \quad T \geq 5\,°F.$$

Data for temperatures below 5°F is not available in the NEEP database. For a single-stage heat pump, it is common for the COP to fall rapidly to 1 below 5 °F (equivalent to operating as an electric resistance heater).[13] However, a cold climate heat pump, typically with two-stage compressors, can maintain a higher COP in colder temperatures.[10] We conservatively assume that the majority of heat pump installations are single-stage and rely on fuel switching (to resistive electricity) when the temperature falls below 5°F. We then calculate the heat pump energy costs h_i as follows:

$$h_i = Pe_i \cdot UA \cdot \sum_{j=1}^{8760} \frac{HDH_{i,j}}{COP(T_{i,j})}, \quad i = 1, 2, ..., N_c,$$

where Pe_i is the electricity price and $T_{i,j}$ is the typical meteorological year temperature at hour j and county i.

Natural gas. Energy costs in counties where natural gas is the primary heating fuel are calculated with state average residential prices and heating content of natural gas delivered to residential customers. We assume a natural gas furnace with average efficiency (90%, based on the National Residential Efficiency Measures Database)[55] and calculate the annual cost (c_i) as follows:

$$c_i = Q_i \cdot \frac{Pg_i}{HC_i \cdot \eta_g}, \quad i = 1, 2, ..., N_c,$$

where Q_i is the annual heating load (in kWh), Pg_i is the utility gas price (in USD/thousand cubic foot), HC_i is the average heating content (in kWh/thousand cubic foot), and η_g is the natural gas furnace efficiency for a county i.

Electric resistance. Energy costs in counties where electricity is the primary fuel (using an electric resistance heater) are calculated as follows:

$$c_i = Q_i \cdot Pe_i \quad i = 1, 2,..., N_c,$$

where Q_i is the annual heating load (in kWh) and Pe_i is the electricity price (in USD/kWh).

Other delivered fuels. Energy costs in counties where other heating fuels (i.e., fuel oil, propane, or wood) are the primary heating source were calculated using reported prices by the U.S. State Energy Data System (SEDS) in USD/kWh.[56] For propane and fuel oil furnaces, we use a heating device efficiency of 88%, which is the average efficiency found in the National Residential Efficiency Measures Database. For wood space heaters, we use an average efficiency of 79% for wood central heaters reported by the EPA-certified wood stove database.[57] Energy costs (c_i) are calculated as follows:

$$c_i = Q_i \frac{Po_i}{\eta_o},$$

where Q_i is the annual heating load (in kWh), Po_i is the other fuels price (in USD/kWh per county), and η_o is the heating device efficiency of other fuels.

7.4 Energy savings

We estimate the net energy bill savings from switching to a heat pump compared to the current primary heating fuel across the U.S. at the county scale. An economic lifetime of 25 years and a private discount rate of 7% is assumed to estimate lifetime savings or added costs in our base case (see below for a discussion of our sensitivity analysis). Therefore, the lifetime savings or added costs are calculated, as the total present value, as follows:

$$s_i = \left(c_i - h_i\right) \cdot \left(1 - (1 + r)^{-n}\right)/r, \quad i = 1, 2,..., N_c,$$

where s_i are the lifetime fuel cost when switching to a heat pump in a county i, c_i is the current annual energy cost, and h_i is the annual energy of a heat pump, n are the economic lifetime years, and r is the discount rate.

7.5 Uncertainty analysis

Many inputs that impact the net bill savings of heat pumps relative to other heating technologies are subject to uncertainty, including electricity and fuel pricing and heating device efficiency. To assess the effects of these uncertainties on the sign of the net benefits, we use a Monte Carlo simulation. We use the following probability distributions for parameters in the analysis (with the exception of typical meteorological data, which for simplicity is deterministic in our analysis):

- ***Heat pump efficiency.*** We use a triangular distribution for the slope of the heat pump COP function with minimum, average and maximum slope values of 0.03, 0.05, and 0.07, respectively, taken from the NEEP database. This yields a COP no higher than 5

and no less than 3 for an operating temperature of 47°F. The COP value can fall below 3 for operating temperatures lower than 47°F.

- **Other heating device efficiencies.** For natural gas, propane, fuel oil, and wood heaters we use triangular distributions for device efficiencies. We use a minimum efficiency of 78% for natural gas, propane and fuel oil based on the first Federal standard (established in 1992)[58] for residential furnaces, and 58% for wood space heaters (based on the EPA-Certified wood stove database). We use an average efficiency of 80% for natural gas and propane furnaces, 83% for fuel oil furnaces (based on the 2015 Federal standard for residential furnaces), and 79% for wood space heaters (based on the average efficiency in the EPA-certified wood stove database). We use a maximum efficiency of 99% for natural gas and propane, 96.7% for fuel oil furnaces (based on the highest efficiency Energy Star certified furnaces database),[59] and 90% for wood space heaters (based on the maximum efficiency in the EPA-certified wood stove database).
- **Fuel prices.** We use national average residential fuel prices from 2000 to 2020 reported by EIA,[60] relative to 2020, to calculate uncertainty ranges for fuel prices at the state (natural gas, propane, fuel oil, and wood) and county (electricity) level. We calculate the coefficient of variation in the time range for each fuel and use it to construct triangular distributions by setting an uncertainty range as a percentage from 2020 prices in each county. The price coefficients of variation using two standard deviations are: 30% for natural gas, 29% for electricity, 21% for propane, 79% for fuel oil, and 68% for wood.

We simulate 10,000 random samples for our Monte Carlo simulation and separate counties into three categories: (1) *net benefits*, if more than 90% of realizations yield energy savings, (2) *neutral*, when energy savings occur less than 90% and more than 10% of realizations, and (3) *net costs*, if energy savings occur in less than 10% of realizations. The results include 1749, 736, and 623 counties in the net benefits, neutral, and net costs zones.

Section 8: Interpretation of coefficients

Here we describe how to interpret log odds coefficients by transforming them into a percentage change in odds. First, the general logit regression model is

$$log\frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_i x_i + \cdots + \beta_n x_n \text{ ,}$$

where p is the probability of the outcome, β_i are the log odds coefficients (as shown in Figures 3 and 5) and x_i are the values of n predictors. By taking the exponent of the above equation, we can get the odds (Ω) of the outcome,

$$\Omega = \frac{p}{1-p} = exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_i x_i + \cdots + \beta_n x_n) \text{ .}$$

We then let Ω be a function $\Omega(x_i)$ of predictor x_i and a unit change δ as follows:

$$\Omega(x_i + \delta) \; = \; exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_i(x_i + \delta) + \cdots + \beta_n x_n) \; ,$$

which is equivalent to

$$\Omega(x_i + \delta) \; = \; exp(\beta_0)exp(\beta_1 x_1)exp(\beta_2 x_2)exp(\beta_i x_i)exp(\beta_i \delta) \cdots exp(\beta_n x_n) \; .$$

Then, we take the ratio of $\Omega(x_i + \delta)$ and $\Omega(x_i)$, which is the *odds ratio*:

$$\frac{\Omega(x_i + \delta)}{\Omega(x_i)} \; = \; \frac{exp(\beta_0)exp(\beta_1 x_1)exp(\beta_2 x_2)exp(\beta_i x_i)exp(\beta_i \delta)\cdots exp(\beta_n x_n)}{exp(\beta_0)exp(\beta_1 x_1)exp(\beta_2 x_2)exp(\beta_i x_i)\cdots exp(\beta_n x_n)} = exp(\beta_i \delta).$$

The odds ratio is a measure of association of between the odds of the outcome and a predictor x_i, increased by a unit change δ, while holding the rest of the predictors constant. Note that there is no assumption about the level of the rest of predictors (as long as they are the same in the numerator and denominator of the ratio). Further, as we discussed in the main results, it is useful to calculate the percentage change of odds as follows:

$$100\frac{\Omega(x_i + \delta) - \Omega(x_i)}{\Omega(x_i)} = 100 \cdot (exp(\beta_i \delta) - 1).$$

The percentage change in odds of the outcome allows us to compare how likely is the outcome to occur (i.e., heat pump access) when increasing the value of a predictor (e.g., the percentage of Black population) against *not* increasing its value.

Section 9: Additional regression results

As robustness checks, we performed logistic regressions on our national dataset using a basic model (9.1) (race/ethnicity percent, climate, energy prices, and state dummies) and then sequentially adding relevant variables, such as income (9.2), building age (9.3), tenancy status (9.4), home value (9.5), and housing type (9.6) one by one. We also performed an additional logistic regression by replacing the continuous variable "building age" with a categorical variable for buildings built each decade from pre-1940s to the 2000s (9.7). The categorical building data was extracted from the American Community Survey (ACS) 2016-2020 five-year data at the census level (see Figure 2 in the main paper for the relationship between the continuous building age variable with heat pump access). We also performed a regression by replacing the natural gas price with natural gas access as a binary variable (9.8). Finally, we performed logistic regressions considering interaction terms as follows: (9.9) race/ethnicity percent interaction with income, (9.10) race/ethnicity percent interaction with tenancy status, (9.11) race/ethnicity percent interaction with building age, and (9.12) race/ethnicity percent interaction with income, tenancy status, and building age simultaneously.

9.1 Basic model (race/ethnicity, climate, energy prices, and state dummies)

Table 9.1. Coefficient estimates and standard errors for the basic national logistic regression model for heat pump use. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations).

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.551***	0.004
Asian (%)	-4.763***	0.015
Hispanic (%)	-1.083***	0.009
Multiracial (%)	-3.138***	0.024
Pacific Islanders (%)	-7.422***	0.165
Native (%)	1.544***	0.045
Other (%)	-6.242***	0.097
Heating degree-days (-)	-0.53***	0.005
Cooling degree-days (-)	-0.317***	0.005
Natural gas price (-)	0.052***	0.001
Electricity price (-)	0.212***	0.002
Constant	-5.005***	0.046
State dummies	Yes	-
Housing type dummies	No	-
Pseudo R^2	0.3032	-
Observations	52,356,989	-

9.2 Basic model and income

Table 9.2. Coefficient estimates and standard errors for the basic national logistic regression model for heat pump use controlling for income. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations).

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.533***	0.005
Asian (%)	-4.295***	0.016
Hispanic (%)	-1.172***	0.01
Multiracial (%)	-3.058***	0.024
Pacific Islanders (%)	-8.03***	0.168
Native (%)	1.594***	0.046
Other (%)	-6.234***	0.1
Heating degree-days (-)	-0.492***	0.005

Cooling degree-days (-)	-0.291***	0.005
Natural gas price (-)	0.038***	0.001
Electricity price (-)	0.213***	0.002
Log Income	7.736***	0.072
(Log Income)^2	-0.348***	0.003
Constant	-48.08***	0.411
State dummies	Yes	-
Housing type dummies	No	-
Pseudo R^2	0.3040	-
Observations	52,285,121	-

9.3 Basic model and building age

Table 9.3. Coefficient estimates and standard errors for the basic national logistic regression model for heat pump use controlling for building age. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations).

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.278***	0.005
Asian (%)	-5.826***	0.016
Hispanic (%)	-0.736***	0.01
Multiracial (%)	-3.364***	0.025
Pacific Islanders (%)	-6.878***	0.169
Native (%)	2.187***	0.044
Other (%)	-6.421***	0.098
Heating degree-days (-)	-0.615***	0.006
Cooling degree-days (-)	-0.349***	0.005
Natural gas price (-)	0.002	0.001
Electricity price (-)	0.228***	0.002
Building age (-)	-0.024***	0
Constant	-4.128***	0.046
State dummies	Yes	-
Housing type dummies	No	-
Pseudo R^2	0.3313	-
Observations	51,334,229	-

9.4 Basic model and tenancy status

Table 9.4. Coefficient estimates and standard errors for the basic national logistic regression model for heat pump use controlling for tenancy status. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.343***	0.005
Asian (%)	-4.614***	0.015
Hispanic (%)	-0.767***	0.009
Multiracial (%)	-2.727***	0.024
Pacific Islanders (%)	-6.373***	0.165
Native (%)	1.576***	0.045
Other (%)	-6.031***	0.095
Heating degree-days (-)	-0.549***	0.005
Cooling degree-days (-)	-0.312***	0.005
Natural gas price (-)	0.043***	0.001
Electricity price (-)	0.204***	0.002
Rented (%)	-0.562***	0.005
Vacant (%)	0.795***	0.011
Constant	-4.959***	0.046
State dummies	Yes	-
Housing type dummies	No	-
Pseudo R^2	0.3040	-
Observations	52,356,193	-

9.5 Basic model and home value

*Table 9.5. Coefficient estimates and standard errors for the basic national logistic regression model for heat pump use controlling for home value. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations).*

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.507***	0.004
Asian (%)	-4.933***	0.016
Hispanic (%)	-1.061***	0.009
Multiracial (%)	-3.134***	0.024
Pacific Islanders (%)	-7.206***	0.165
Native (%)	1.62***	0.045
Other (%)	-6.36***	0.097
Heating degree-days (-)	-0.517***	0.005
Cooling degree-days (-)	-0.327***	0.005

Natural gas price (-)	0.043***	0.001
Electricity price (-)	0.212***	0.002
Log Home value	0.045***	0.001
Constant	-5.587***	0.046
State dummies	Yes	-
Housing type dummies	No	-
Pseudo R^2	0.3025	-
Observations	52,145,047	-

9.6 Basic model and housing type

*Table 9.6. Coefficient estimates and standard errors for the basic national logistic regression model for heat pump use controlling for housing type. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations).*

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.565***	0.004
Asian (%)	-4.95***	0.015
Hispanic (%)	-1.144***	0.009
Multiracial (%)	-3.145***	0.024
Pacific Islanders (%)	-7.276***	0.165
Native (%)	1.43***	0.046
Other (%)	-6.271***	0.097
Heating degree-days (-)	-0.544***	0.005
Cooling degree-days (-)	-0.329***	0.005
Natural gas price (-)	0.049***	0.001
Electricity price (-)	0.212***	0.002
Constant	-5.054***	0.046
State dummies	Yes	-
Housing type dummies	Yes	-
Pseudo R^2	0.3042	-
Observations	52,356,989	-

9.7 Complete model with building age as categorical variable

*Table 9.7. Coefficient estimates and standard errors for the complete national logistic regression model for heat pump use replacing building age with categorical variables. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations).*

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.401***	0.005
Asian (%)	-5.219***	0.018
Hispanic (%)	-0.917***	0.01
Multiracial (%)	-2.976***	0.025
Pacific Islanders (%)	-8.278***	0.171
Native (%)	1.239***	0.046
Other (%)	-5.785***	0.097
Heating degree-days (-)	-0.513***	0.005
Cooling degree-days (-)	-0.162***	0.005
Natural gas price (-)	-0.032***	0.001
Electricity price (-)	0.189***	0.002
Log Home value	0.056***	0.001
Rented (%)	-0.458***	0.006
Vacant (%)	0.422***	0.012
Buildings pre 1940 (%)	-1.652***	0.011
Buildings 1940s (%)	-2.423***	0.021
Buildings 1950s (%)	-2.319***	0.014
Buildings 1960s (%)	-2.371***	0.014
Buildings 1970s (%)	-0.166***	0.011
Buildings 1980s (%)	1.244***	0.01
Buildings 1990s (%)	-0.069***	0.01
Buildings 2000s (%)	0.193***	0.012
Log Income	1.979***	0.069
(Log Income)^2	-0.117***	0.003
Constant	-12.76***	0.392
State dummies	Yes	-
Housing type dummies	No	-
Pseudo R^2	0.3251	-
Observations	52,076,215	-

9.8 Natural gas access

Table 9.8. Coefficient estimates and standard errors for the complete national logistic regression model for heat pump use replacing natural gas prices with a binary variable denoting natural gas access. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations).

Variable	Log Odds Coefficient	S.E.

Black (%)	-1.595***	0.005
Asian (%)	-4.48***	0.016
Hispanic (%)	-0.916***	0.009
Multiracial (%)	-2.941***	0.021
Pacific Islanders (%)	-8.277***	0.151
Native (%)	2.407***	0.024
Other (%)	-4.558***	0.081
Heating degree-days (-)	-0.902***	0.005
Cooling degree-days (-)	-0.391***	0.004
Natural gas access	-0.111***	0.002
Electricity price (-)	0.234***	0.002
Log Home value	0.034***	0.001
Rented (%)	-0.531***	0.006
Vacant (%)	0.065***	0.008
Building age (-)	-0.733***	0.001
Log Income	3.127***	0.061
(Log Income)^2	-0.167***	0.003
Constant	-20.056***	0.368
State dummies	Yes	-
Housing type dummies	Yes	-
Pseudo R^2	0.3295	-
Observations	62,138,170	-

9.9 Race percent interaction with income

Table 9.9. Coefficient estimates and standard errors for the complete national logistic regression model for heat pump use and interactions of race percent with income. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** $p<0.01$, ** $p<0.05$, * $p<0.1$). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations). An asterisk, "*", between two variables denotes an interaction, for example, "Hispanic * rented".

Variable	Log Odds Coefficient	S.E.
Black (%)	-12.164***	0.110
Asian (%)	-3.189***	0.413
Hispanic (%)	18.327***	0.221
Multiracial (%)	3.839***	0.595
Pacific Islanders (%)	-32.039***	5.197
Native (%)	15.07***	1.218
Other (%)	14.515***	2.548
Black * log income	0.974***	0.010
Asian * log income	-0.084**	0.036

Variable	Log Odds Coefficient	S.E.
Hispanic * log income	-1.76***	0.020
Multiracial * log income	-0.6***	0.053
Pacific Islanders * log income	2.131***	0.470
Native * log income	-1.304***	0.114
Other * log income	-1.805***	0.228
Heating degree-days (-)	-0.495***	0.005
Cooling degree-days (-)	-0.149***	0.005
Natural gas price (-)	-0.014***	0.001
Electricity price (-)	0.212***	0.002
Log Home value	0.017***	0.001
Rented (%)	-0.395***	0.007
Vacant (%)	0.985***	0.011
Building age (-)	-0.733***	0.001
Log Income	2.331***	0.083
(Log Income)^2	-0.126***	0.004
Constant	-15.71***	0.473
State dummies	Yes	-
Housing type dummies	Yes	-
Pseudo R^2	0.3343	-
Observations	52,076,215	--

9.10 Race percent interaction with tenancy status

Table 9.10. *Coefficient estimates and standard errors for the complete national logistic regression model for heat pump use and interactions of race percent with tenancy status. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations). An asterisk, "*", between two variables denotes an interaction, for example, "Hispanic * rented".*

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.282***	0.01
Asian (%)	-4.556***	0.028
Hispanic (%)	-1.047***	0.022
Multiracial (%)	-2.355***	0.047
Pacific Islanders (%)	-13.377***	0.414
Native (%)	1.707***	0.133
Other (%)	-4.516***	0.193
Black * rented	1.051***	0.023
Asian * rented	0.522***	0.082
Hispanic * rented	-0.249***	0.05

Multiracial * rented	-0.441***	0.131
Pacific Islanders * rented	9.291***	0.832
Native * rented	-1.353***	0.364
Other * rented	-0.283	0.553
Black * vacant	-12.399***	0.132
Asian * vacant	6.312***	0.495
Hispanic * vacant	5.201***	0.135
Multiracial * vacant	-8.094***	0.281
Pacific Islanders * vacant	45.291***	2.72
Native * vacant	-0.274	0.454
Other * vacant	-25.853***	1.341
Heating degree-days (-)	-0.516***	0.005
Cooling degree-days (-)	-0.153***	0.005
Natural gas price (-)	-0.02***	0.001
Electricity price (-)	0.215***	0.002
Log Home value	0.015***	0.001
Rented (%)	-0.608***	0.011
Vacant (%)	1.313***	0.016
Building age (-)	-0.735***	0.001
Log Income	2.433***	0.077
(Log Income)^2	-0.133***	0.003
Constant	-15.877***	0.437
State dummies	Yes	-
Housing type dummies	Yes	-
Pseudo R^2	0.3342	-
Observations	51,139,213	-

9.11 Race percent interaction with building age

Table 9.11. *Coefficient estimates and standard errors for the complete national logistic regression model for heat pump use and interactions of race percent with building age. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations). An asterisk, "*", between two variables denotes an interaction, for example, "Hispanic * rented".*

Variable	Log Odds Coefficient	S.E.
Black (%)	-1.487***	0.005
Asian (%)	-3.169***	0.018
Hispanic (%)	-1.108***	0.011
Multiracial (%)	-2.87***	0.028

Variable	Log Odds Coefficient	S.E.
Pacific Islanders (%)	-7.279***	0.177
Native (%)	0.464***	0.068
Other (%)	-6.583***	0.12
Black * building age	-0.273***	0.006
Asian * building age	2.341***	0.016
Hispanic * building age	-0.458***	0.013
Multiracial * building age	-0.119***	0.033
Pacific Islanders * building age	2.686***	0.207
Native * building age	-1.842***	0.08
Other * building age	-1.873***	0.135
Heating degree-days (-)	-0.497***	0.005
Cooling degree-days (-)	-0.155***	0.005
Natural gas price (-)	-0.016***	0.001
Electricity price (-)	0.213***	0.002
Log Home value	0.014***	0.001
Rented (%)	-0.434***	0.007
Vacant (%)	0.993***	0.011
Building age (-)	-0.737***	0.002
Log Income	2.952***	0.071
(Log Income)^2	-0.155***	0.003
Constant	-19.052***	0.405
State dummies	Yes	-
Housing type dummies	Yes	-
Pseudo R^2	0.3343	-
Observations	51,139,213	-

9.12 Race percent interaction with income, tenancy, and building age

Table 9.11. *Coefficient estimates and standard errors for the complete national logistic regression model for heat pump use and interactions of race percent with income, tenancy status, and building age. The marking in the coefficient estimates denotes the significance of the coefficient (i.e., *** p<0.01, ** p<0.05, * p<0.1). Variables labeled "-" are dimensionless and have been standardized (see Table 1 for means and standard deviations). An asterisk, "*", between two variables denotes an interaction, for example, "Hispanic * rented".*

Variable	Log Odds Coefficient	S.E.
Black (%)	-21.37***	0.171
Asian (%)	-17.50***	0.508
Hispanic (%)	26.74***	0.268
Multiracial (%)	17.20***	0.771
Pacific Islanders (%)	-139.1***	7.331
Native (%)	24.60***	1.668

Other (%)	51.24***	2.864
Black * income	1.721***	0.015
Asian * income	1.232***	0.043
Hispanic * income	-2.471***	0.024
Multiracial * income	-1.676***	0.067
Pacific Islanders * income	11.02***	0.635
Native * income	-2.146***	0.147
Other * income	-4.878***	0.248
Black * rented	3.459***	0.030
Asian * rented	1.313***	0.092
Hispanic * rented	-2.405***	0.056
Multiracial * rented	-2.886***	0.159
Pacific Islanders * rented	19.98***	1.079
Native * rented	-3.220***	0.424
Other * rented	-5.220***	0.632
Black * vacant	-4.559***	0.137
Asian * vacant	3.704***	0.532
Hispanic * vacant	1.247***	0.143
Multiracial * vacant	-12.66***	0.334
Pacific Islanders * vacant	79.08***	3.003
Native * vacant	-3.769***	0.528
Other * vacant	-39.05***	1.431
Black * building age	-0.108***	0.006
Asian * building age	2.563***	0.016
Hispanic * building age	-0.511***	0.012
Multiracial * building age	-0.234***	0.034
Pacific Islanders * building age	2.259***	0.211
Native * building age	-1.791***	0.080
Other * building age	-2.013***	0.131
Heating degree-days (-)	-0.485***	0.005
Cooling degree-days (-)	-0.133***	0.005
Natural gas price (-)	-0.00568***	0.002
Electricity price (-)	0.206***	0.002
Log Home value	0.0148***	0.001
Rented (%)	-0.666***	0.012
Vacant (%)	1.297***	0.016
Building age (-)	-0.743***	0.002
Log Income	1.957***	0.085
$(Log\ Income)^2$	-0.112***	0.004
Constant	-13.22***	0.482

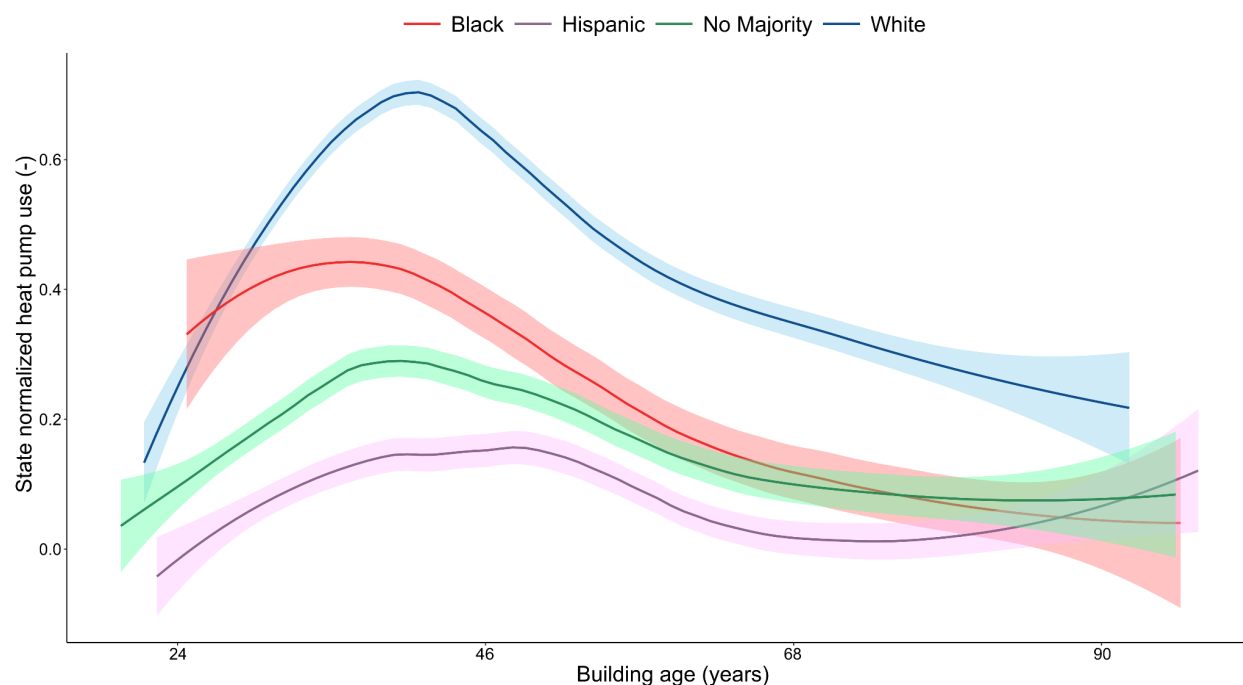|		
State dummies	Yes	-
Housing type dummies	Yes	-
Pseudo R^2	0.3364	-
Observations	51,139,213	-

Section 10: Supplementary Figures

Figure S1. *Relationship between building age and heat pump access using a nonparametric analysis (see Figure 2 in the main paper for building age relationship with heat pump access using a parametric analysis). Lines show LOESS fits and shaded regions show 90% confidence intervals. For better visualization, the building age has been restricted to the middle 98 percentile.*
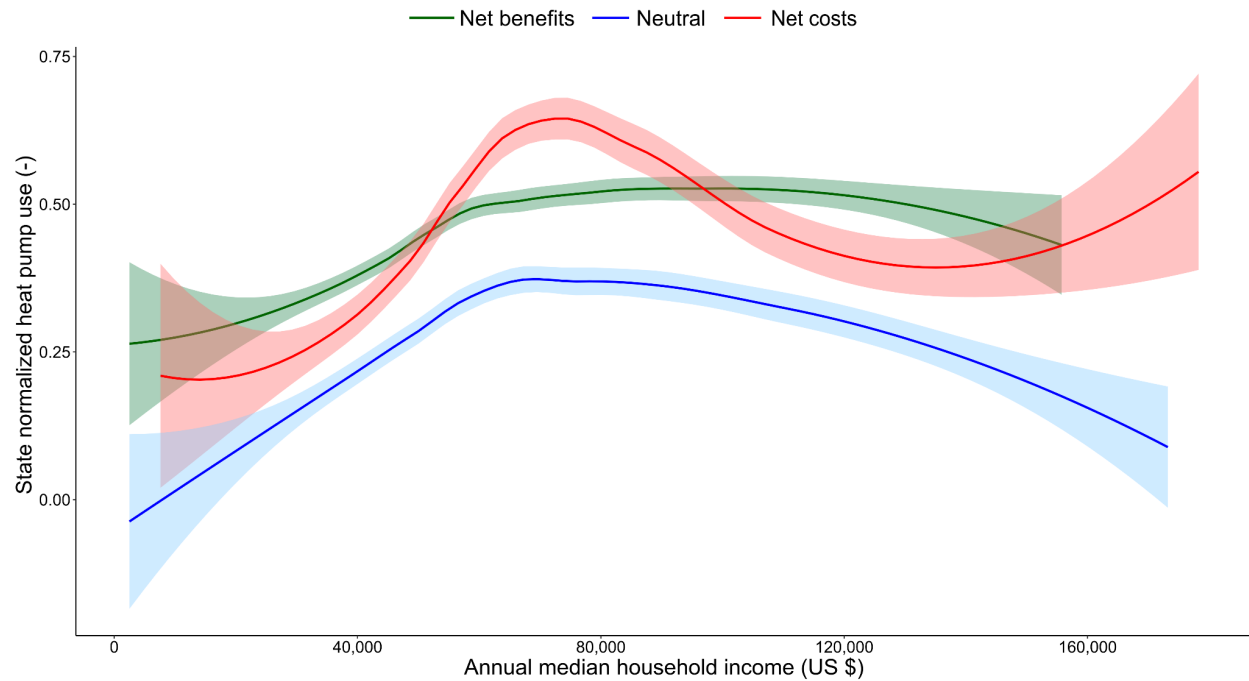
Figure S2. *Relationship between income and heat pump access for each heat pump cost/benefit region using a nonparametric analysis (see Figure 5 in the main paper for comparison). Lines show LOESS fits and shaded regions show 90% confidence intervals.*

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