

ABSTRACT

Title of Dissertation: THREE ESSAYS ON FACILITATING
ELECTRIFICATION AND ENERGY
EFFICIENCY FROM THE DEMAND SIDE

Xingchi Shen, Doctor of Philosophy, 2022

Dissertation directed by: Prof. Yueming (Lucy) Qiu
School of Public Policy

To tackle climate change, one of the basic decarbonization strategies is to decarbonize end-use applications through electrification and energy efficiency. This dissertation comprises three essays focused on the effectiveness and implementation of the interventions aimed at electrification and energy efficiency in the building sector of the demand side. It is not easy to facilitate the transition to energy efficiency and electrification. In the building sector, much literature has found the “energy efficiency gap”, meaning that there is a persistent gap between the level of energy efficiency investment that is projected to save money and the investment that actually occurs despite the benefits from energy-efficiency investments. In many situations, the energy efficiency upgrade is in conjunction with electrification.

Two types of interventions have been widely utilized to help close the “energy efficiency gap” and “electrification gap” in the building sector: price-based incentives and information-provision interventions. In my dissertation, the first essay focuses on (price-based) subsidy

interventions while the other two essays focus on information-provision interventions to alter consumers' energy demand.

The first essay aims to evaluate the effectiveness of the subsidies (rebate and loan programs) on residential air-source heat pump adoption based on the evidence from North Carolina of U.S. Many national, state-level, and city-level decarbonization plans include the transition to heat pumps. The rebate and loan programs are the two widely-adopted incentives for residential heat pumps in the U.S. Using the method of Difference-in-Differences (DID) in conjunction with spatial discontinuity, this essay estimates the impact of a rebate program (\$300-450 per system) on heat pump adoption rate and compares it with the effect of two loan programs (with different annual interest rates: 9% and 3.9%). I find that the rebate program increases the adoption density by 13% in a year and shows advantages in increasing the heat pump adoption rate compared to the two loan programs.

The second essay finds a positive house price premium associated with air-source heat pump installations in the U.S., which policymakers can use to provide information campaigns to influence the adoption of heat pumps. In this essay, I apply the DID method and use a sample of 450,000 homes across 23 states of the U.S. to estimate the heat pump-induced house sales price premium. Residences with an air-source heat pump enjoy a 4.3-7.1% (or \$10,400 - \$17,000) price premium on average. Policymakers can use the information about potential price premiums to influence consumer choices, in addition to traditional energy guides, which typically focus on fuel costs.

The third essay investigates the effectiveness of another type of information-provision campaign – special environmental events. Special environmental events, such as Earth Hour, World Environment Day, and Chinese National Energy Saving Week, can be regarded as a form

of “nudge” to arouse people’s awareness of environmental protection and energy efficiency/conservation. Using a two-stage local linear method, I estimate the impacts of the three special environmental events on short-run electricity-saving behaviors using high-frequency smart meter data in Shanghai, China, for both residential and commercial consumers. I find that World Environment Day and National Energy Saving Week caused commercial users to reduce their electricity consumption by 1.35 kWh/hour and 0.6 kWh/hour intra-event, around 17% and 8% reduction compared to average consumption. Earth Hour did not lead to significant energy-saving effects for both residential and commercial users.

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EFFICIENCY FROM THE DEMAND SIDE

by

Xingchi Shen

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Advisory Committee:

Professor Yueming (Lucy) Qiu, Chair
Professor Nathan Hultman
Professor Anand Patwardhan
Professor Kavita Surana
Professor Joshua Linn

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Chapter 1: Introduction

1. Research background and motivation

Climate change and global warming have become globally urgent challenges. The increase in global average temperature must be kept below 1.5 degrees Celsius above the pre-industrial level to avoid irreversible environmental damage (Masson-Delmotte, V. et al., 2018). This requires us to reduce, capture and sequester carbon emissions from burning fossil fuels. There are three basic strategies to realize the deep-decarbonization of the economy: First, decarbonize the power generation through developing and integrating more clean renewable energy into our electricity grid; Second, decarbonize end-use applications through electrification and energy efficiency; Third, enhance the carbon storage capacity of the environment (Hultman et al., 2019; Denis et al., 2015). My dissertation is focused on the second basic decarbonization strategy which aims to facilitate energy efficiency and electrification from the demand side in the building sector.

It is not easy to facilitate this transition to energy efficiency and electrification. In the building sector, much literature has found the “energy efficiency gap”, meaning that there is a persistent gap between the level of energy efficiency investment that is projected to save money (such as installing an energy star qualified refrigerator, clothes washer, dishwasher, etc.), and the investment that actually occurs despite the benefits from energy-efficiency investments (Fowle et al., 2018). In many situations, the energy efficiency upgrade is in conjunction with electrification. Electrifying some fossil-fuel-burning applications can also bring energy fuel cost savings based on engineering model projection, such as replacing natural gas furnaces with energy-efficient heat pumps and replacing gasoline vehicles with electric vehicles. However, the penetration rate of

these energy efficient and electric applications is still low in the actual world. Much literature contributes to the explanation of “energy efficiency gap”. Common explanations focus on market failures, such as imperfect information, split incentive problems, consumers’ inattention, and other consumer behaviors (e.g., Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Gerarden et al., 2015).

Two types of interventions have been widely utilized to close the “energy efficiency gap” and “electrification gap” in the building sector, which are price-based incentives and non-price-based incentives. For the price-based incentives, the most widely adopted approach by the government and utilities is to subsidize the adoption of energy-efficient electric applications. The subsidies focus on changing relative prices as the major force altering energy demand and have been proved to be very effective, but suffer from expensive implementation costs and possible inequitable outcomes across populations. For the non-price-based incentives, building codes, mandatory standards, and information campaigns have been widely applied. Particularly, academics and policymakers are increasingly interested in using “social nudges” – such as information provision and persuasion – to alter consumer behaviors. Nudges are typically inexpensive compared to price-based approaches. As Bertrand et al. (2010) stated, carefully crafted psychological cues can exert significant effects on consumer demand that are comparable to large changes in relative prices (LaRiviere et al., 2014).

My dissertation contributes to promoting the effectiveness and justness of the interventions that encourage electrification and energy efficiency from the demand side based on evidence from both China and the U.S.

2. Introduction to three essays

My dissertation is composed of three essays focused on the effectiveness of the interventions mentioned above towards energy efficiency and electrification, respectively. The first essay focuses on subsidy interventions, while the other two essays focus on information-provision campaigns to alter consumers' energy demand. The detailed introduction to each essay is as follows.

The first essay aims to evaluate the effectiveness of the subsidies (rebate and loan programs) on residential air-source heat pumps adoption based on the evidence from North Carolina of the U.S. Many studies have proved that electric heat pumps are a practical and energy-efficient alternative to natural-gas furnaces or boilers for space heating (Davis et al., 2018; Lucon et al., 2014; MacKay, 2009; "The heat is on," 2007). Many national, state-level, and city-level plans for decarbonization include the transition to heat pumps. For example, Finland, Ireland, the Netherlands, and Massachusetts in the U.S. all have introduced plans to phase out natural gas and electrify buildings via heat pumps. The rebate and loan programs are the two widely-adopted incentives for heat pumps in the U.S. Very few studies estimate the effects of these incentives on heat pump adoption. This essay provides the first rigorous estimate of the rebate's impact on residential air-source heat pump adoption and compares the rebate's effect with that of two loan programs. Using the approach of difference-in-differences (DID) in conjunction with spatial discontinuity, I find that a rebate program (\$300-\$450) increases the adoption rate by 13% in a year period. The rebate program (\$300-\$450) shows advantages in effectiveness to promote the growth of heat pumps compared to the other two loan programs (Annual percentage rate: 9%, 3.9%). I also find that the rebate program is less effective for low-income households than for high-income households.

Estimating the benefits of green home improvements (e.g., heat pump adoption) is not possible without accurate estimates of their impact on house prices. The second essay aims to find a positive house price premium associated with air-source heat pump installations in the U.S., which can be used by policymakers to provide information campaigns to influence the adoption of heat pumps. In this essay, I leverage a large dataset including over 150 million residential properties and 374 million transaction records all over the U.S. I apply the DID method and use a sample of 45,000 homes across 23 states of the U.S. to estimate the heat pump-induced house sales price premium. I find that residences with an air-source heat pump enjoy a 4.3-7.1% (or \$10,400 - \$17,000) price premium on average. Residents who are environmentally conscious, middle class, and live in regions with mild climate are more likely to pay a larger price premium. The estimated price premiums are larger than the calculated total social benefits of switching to heat pumps. More importantly, my findings provide a new incentive for heat pump adoption. Policymakers can use the information about potential price premiums to influence consumer choices to help close the energy efficiency and electrification gap, in addition to traditional energy guides, which typically focus on fuel costs.

The third essay investigates the effectiveness of another type of information-provision campaign – special environmental events. Special environmental events, such as Earth Hour, World Environment Day, and Chinese National Energy Saving Week, can be regarded as a form of “nudge” in order to arouse people’s awareness of environmental protection and energy efficiency/conservation. These events have been globally popular with decades of history. A large number of governments and NGOs have been spending great efforts on organizing them. However, few studies provide rigorous analysis on it. This essay provides the first empirical evidence of the impacts of special environmental events on consumers’ short-run electricity saving behaviors

using high-frequency (hourly and daily) electricity consumption data in 2017 in Shanghai, China, for both residential and non-residential sectors. I find that World Environment Day and National Energy Saving Publicity Week caused commercial users to reduce their electricity consumption by 1.35 kWh/hour and 0.6 kWh/hour intra-event, around 17% and 8% reduction compared to average consumption, but the impacts decayed rapidly once the events ended. Earth Hour did not lead to significant energy-saving effects for both residential and commercial users. In addition, I examine detailed activities implemented during these events to understand the heterogeneous impacts using social media and policy documents data. I find that most activities during the World Environment Day and National Energy Saving Publicity Week are directly related to the knowledge and skills of environmental protection and energy saving, while most activities during the Earth Hour are only symbolic behaviors (like turning off lights). My analysis provides suggestive evidence that activities providing knowledge and skills may promote more energy-saving behaviors compared to symbolic activities. My results suggest that policymakers should combine the merits of symbolic campaigns and knowledge-based campaigns when they aim to organize large-scale environmental campaigns.

3. Contribution to the literature

My dissertation contributes to the literature on the “energy efficiency gap”, the value of energy investment, and the effect of price-based incentives on energy investment. Many studies use hedonic pricing methods to value energy technologies and energy efficiency investment, such as installing solar panels or solar water heaters, energy efficiency rating or green-building labeling

(Aydin et al., 2018; Qiu et al., 2017; Hoen et al., 2013; Dastrup et al., 2012; Walls et al., 2017; Kahn and Kok, 2014; Deng et al., 2012; Deng and Wu, 2014; Brounen and Kok, 2011; Jayantha and Man, 2013; Eichholtz et al., 2012, 2010; Costa et al., 2018). Some studies investigate the subsidy effects on residential energy technology adoption, such as on solar panels (Crago et al., 2017; Gillingham & Tsvetanov, 2019) and energy efficiency measures (Datta and Gulati, 2014; Houde and Aldy, 2017). To the best of my knowledge, my dissertation is the first study to examine the subsidy effects on heat pump adoption and the house resale price premium of heat pumps.

My dissertation also contributes to the literature on the effectiveness of information-based interventions aimed at energy efficiency/conservation. Studies have examined the effectiveness of different non-price-based interventions, such as commitment (Katzev & Johnson, 1983), goal setting (Becker, 1978; McCalley and Midden, 2002), self-feedback (like energy bill reminder (Jesoe & Rapson, 2014)), comparative feedback (like Opower letters (Allcott, 2011; Costa and Kahn, 2013; Allcott and Rogers, 2014; LaRiviere et al., 2014) and water use comparison messages (Ferraro and Price, 2013)). To the best of my knowledge, the third essay in my dissertation is the first study to estimate the impact of big environmental events on consumers' energy saving behaviors.

The research objects of my dissertation are representative. The first and second essays are evidenced from the U.S. while the third essay is based on evidence from China. The U.S. and China are the two largest carbon emitters in the world in 2021. Investigating the approaches to promote the transition to electrification and energy efficiency in these two countries is relevant and urgent.

Chapter 2: Essay 1 - The Effect of Rebate and Loan Incentives on Residential Heat Pump Adoption: Evidence from North Carolina

Abstract

Electrification can promote deep decarbonization to tackle climate change with a cleaner power grid. Electric heat pumps provide a feasible and energy-efficient way to replace fossil-fuel furnaces for space heating. Rebate and loan programs are the two most widely used incentives for residential heat pump installations in the U.S. This study compares the impacts of rebate and loan incentives on residential air-source heat pump adoption in North Carolina. First, my results show that the rebate program (\$300-\$450 per system) increases the adoption density by 13% in a year. Second, I find that the rebate program is more effective in promoting heat pump adoption for average consumers than two loan programs (annual loan interest rate: 9%, 3.9%) under the assumption of comparable demand for replacing heating equipment in my samples. Third, I find the rebate program is less effective for low-income households than high-income households. Last, I compare the rebate with the loan in terms of cost-effectiveness.

1. Introduction

Climate change and global warming have become urgent worldwide challenges. Actions are needed to stop, reduce, and capture emissions of CO₂ to stabilize the earth's temperature (IPCC, 2018). Electrifying fossil-fuel-burning appliances with more renewable energy integrated into the power grid provides one pathway to promote the "deep decarbonization of the economy" (Denis et al., 2015; Hultman et al., 2019). In the context of space heating, reducing emissions from large sources (e.g., electric plants) is more effective compared to reducing the emissions from distributed

small sources (e.g., tens of millions of small natural gas furnaces across the U.S.). Studies have shown that heat pumps are a practical and energy-efficient alternative to natural-gas furnaces or boilers for space heating (Davis et al., 2018; Lucon et al., 2014; MacKay, 2009). Many national, state, and city-level decarbonization plans have included the transition to heat pumps. For example, Finland, Ireland, Netherlands, and Massachusetts in the U.S. have introduced plans to phase out natural gas and electrify buildings via electric heat pumps.

Heat pumps also bring other potential benefits. In addition to space heating, heat pumps provide an energy-efficient way for space cooling compared to traditional HVAC (Heating Ventilation Air Conditioning) systems. Given the high projected demand for air conditioning in developing countries in the near future (Biardeau et al., 2019), heat pumps can help meet this demand in an energy-efficient way. In northern U.S. regions, high-efficient electric heat pumps can relieve natural gas constraints caused by the high demand for space heating in the winter (Shen et al., 2020). In regions with limited natural gas services availability, heat pumps provide an efficient way for space heating. Moreover, with more intermittent energy sources (e.g., renewable energy sources) intergraded into the power grid in the future, electric heating systems through the installations of heat pumps provide possibilities for remote smart demand management to ensure the stable operation of the grid (Kassakian et al., 2011).

Currently, the penetration rate of residential heat pumps is still low and imbalanced in most U.S. regions. Policymakers and utilities have adopted different incentives to promote the diffusion of heat pump technology. The rebate and low-interest loan programs are the two most widely used incentives for residential heat pump installations according to the Database of State Incentives for Renewables & Efficiency (DSIRE)¹. In the 2020 U.S. presidential election campaign, Joe Biden

¹ The national-level DSIRE database records almost all the incentives for renewable and efficient energy technologies, including heat pumps, for every state in the U.S.

also put these two policies as the prioritized strategy to tackle the climate crisis. He declared to “spur the building retrofit and efficient-appliance manufacturing supply chain by funding direct cash rebates and low-cost financing to upgrade and electrify home appliances” in the transition plan². A better understanding of the actual effect of these incentives is needed to identify effective policies that can facilitate the transition to heat pumps and other low carbon technologies.

This study provides the first empirical evidence of the impact of rebate and loan incentives on air-source heat pump adoption rate (measured by the share of households with the heat pumps) using difference-in-differences (DID), spatial regression discontinuity (RD), and differential trends comparison research designs, leveraging utility borders within the same ZIP code area based on three samples in North Carolina. My panel data contains individual property’s heat pump installation information from 2016-2020. I conduct a rigorous comparative analysis of different impacts between the two widely-used types of incentives. I explore the following research questions: Do the rebate incentives increase residential air-source heat pump adoption? Which policy (between the rebate and the loan) is better in terms of effectiveness in improving adoption rates and cost-effectiveness? What is the mechanism behind the different impacts of these two policies?

This paper makes three primary contributions to the literature. First, my research contributes to the literature on the potential policy options for overcoming barriers to heat pump adoption. Many studies have demonstrated that major barriers to a greater market share of heat pumps include high upfront costs (Kircher & Zhang, 2021), adoption inconvenience (Snape et al., 2015), low performance in extremely cold areas (Aste et al., 2013), and residents’ environmentally friendly awareness (Karytsas, 2018). Several options have been suggested to overcome these

² The 46th President of the U.S., Joe Biden, declares a full list of Administration Priorities on Nov 8, 2020, including approaches to tackle the climate change crisis. Source: <https://buildbackbetter.com/priorities/climate-change/>

barriers, such as initiating a new business model based on heat purchase agreements and third-party ownership (Kircher & Zhang, 2021), setting up building energy performance standards, tax and subsidy policies in favor of heat pumps (Hannon, 2015), and information programs about the house price premium after heat pump adoption (Shen et al., 2021). Following that, my study suggests that rebate and loan programs could help facilitate the adoption of air source heat pumps in the US. Second, I build upon existing studies about policy effects on residential energy technology adoption, such as on solar panels (Crago and Chernyakhovskiy, 2017; Gillingham and Tsvetanov, 2019; O’Shaughnessy et al., 2020), energy efficiency appliances (Datta and Gulati, 2014; Houde and Aldy, 2017), and electric vehicles (Wee et al., 2018; Zambrano-Gutiérrez et al., 2018; Roberson and Helveston, 2020). My study provides the first empirical evidence of policy effect on heat pump adoption. Third, this paper provides a comparison between rebate and loan policies, which are the two most-widely adopted incentives in the U.S for residential heat pumps. Heat pumps cost thousands of dollars more compared to traditional HVAC systems. The higher upfront cost may impede consumers with credit constraints from adopting the technology. Easy access to loans can better relieve consumers’ credit constraints. Low-interest loans and rebates are two different types of subsidies, which can reduce the gap between consumers’ willingness to pay and the actual price of heat pumps. I provide a comparison of the effects and mechanisms of these two incentives.

This study provides four main results. First, I estimate the rebate program’s effect on the residential heat pump adoption rate in North Carolina. A rebate program³ (\$300-\$450 per system) increases the adoption rate by 0.024 (or a 13% increase compared to the pre-treatment period) in

³ The rebate program provided by the Duke Energy utility applies to all kinds of heat pumps for space heating (including air-source heat pumps and geothermal heat pumps). My study only estimates the impact of the rebate on the adoption of air-source heat pumps.

a year. Second, under the assumption of comparable demand for replacing old heating equipment within the buffer area in the sample, I find that the rebate program (\$300-\$450) is more effective for average consumers compared to the other two loan programs⁴ (annual percentage rate (APR) of the loan: 9%, 3.9%). Third, I explore the heterogeneous effects of the rebate program across different income intervals. I find the rebate's effect increases with income. Last, I compare the rebate with the loan in terms of the cost-effectiveness, measured by the dollars spent per heat pump installed caused by the policy, and find that the rebate program is more cost-effective than the two loan programs if the proportions of residents who apply for the rebate and the loan in residents with new heat pump installations are the same.

My results have important policy implications. The U.S. government agencies plan to provide more funding through rebate and loan incentives to spur energy upgrading. My study demonstrates that rebate policies can effectively increase the adoption of heat pumps. Moreover, my study shows that the rebate program is more effective and cost-effective to increase heat pump adoption compared to the two loan programs based on the empirical evidence from North Carolina, though the rebate program is less effective for low-income households. Other innovative policies and supports should be considered for low-income communities. My study also has implications for policies stimulating the adoption of other energy technologies, such as, solar water heating, solar panel, and home battery storage, which are similar to air-source heat pumps with higher upfront costs and longer payback periods compared to traditional low-efficiency technologies.

This article is structured as follows. Section 2 describes the background of heat pump adoption in the U.S. Section 3 constructs a stylized model to understand the mechanism of the incentives. Section 4 describes methodological approaches and data, and Section 5 presents the

⁴ The two loan programs also apply to all types of heat pumps for space heating.

estimated effects. In Section 6, I conduct robustness tests. Section 7 estimates the heterogeneous rebate effects by different income intervals. Section 8 compares the cost-effectiveness of each incentive program. Section 9 concludes the paper with discussion and policy implications.

2. Background on heat pump adoption in the U.S.

The installation of air-source heat pumps has increased for residential space heating in recent years in the U.S. However, the distribution of heat pumps is highly imbalanced. **Figure 2.1** plots the distribution of air-source heat pump density (number of heat pumps per 10K persons) by county in 2020 based on the ZTRAX data from Zillow⁵. The Mountain, South Atlantic, Pacific, and West North Central regions have a higher penetration rate of air-source heat pumps than that in other regions (See **Appendix A** for the air-source heat pump adoption density by the state in the U.S. in 2020). More importantly, the penetration rate of heat pumps in most U.S. regions, including regions with mild climates, is low, which implies a potential large room for growth when more effective policies or incentives are provided. North Carolina's warm climate makes it one of the areas with the most installed heat pumps in the U.S. My study chooses North Carolina so that I have enough observations for robust statistical estimation and inference. Although North Carolina has the most installed heat pumps, its penetration rate is only about 9%, with great potential for further growth. North Carolina is also a representative case for other suitable regions for installing

⁵ Zillow's Assessor and Real Estate Database (Zillow Research, 2020). Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at <http://www.zillow.com/ztrax>. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

heat pumps, such as the Middle Atlantic and Pacific regions. Thus, my results on the incentive effects based on North Carolina can be useful for broader regions.

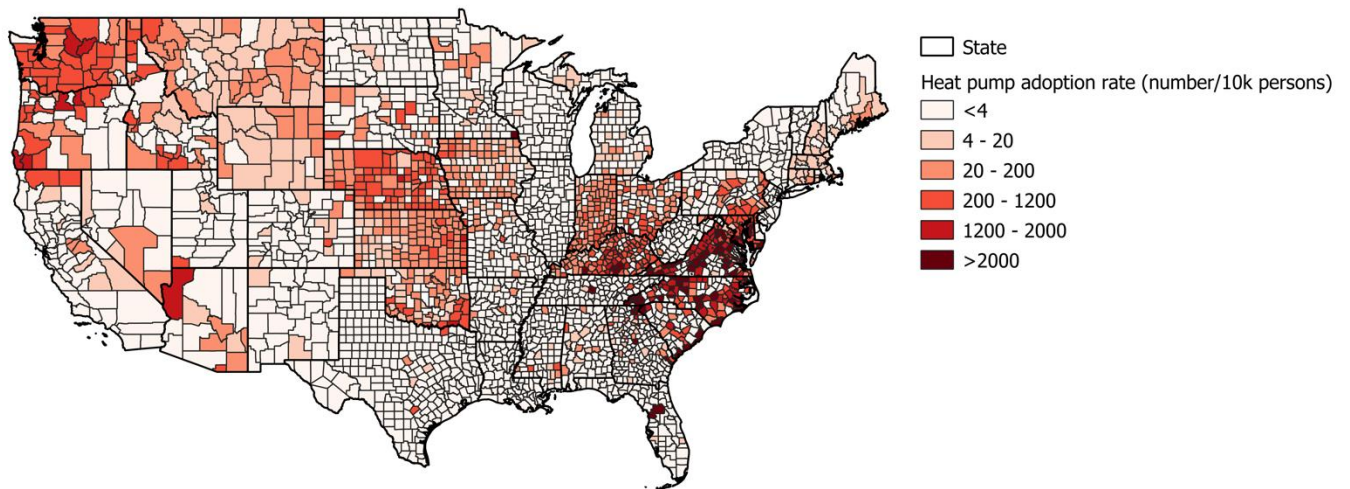


Figure 2.1 The distribution of air-source heat pump adoption density by county in the U.S. in 2020. Data source: ZTRAX database (Zillow’s Assessor and Real Estate Database).

Many factors influence the adoption of residential heat pumps. I first conduct a descriptive analysis and investigate the correlation between the heat pump adoption and a number of explanatory factors by regressing the heat pump adoption density in 2018 (the number of air-source heat pumps per 10K persons) on a set of variables (including personal income per capita, population density, residential electricity price, residential natural gas price, environmental awareness level, heating degree days and cooling degree days) at the county level using the U.S. national dataset (See **Figure 2.2** and **Appendix B**). I obtain the data from the ZTRAX database, Bureau of Economic Analysis, U.S. Department of Commerce, U.S. Energy Information Administration, Yale Program on Climate Change Communication (Howe et al., 2015), and National Oceanic and Atmospheric Administration. I standardize all the independent variables into

variables with 0 mean and 1 standard deviation. **Figure 2.2** plots the estimated coefficients of these variables, representing the change in heat pump adoption density with a standard deviation change of these variables, to identify the relative importance of each factor. I find that the strongest correlation is with climate factors (heating and cooling degree days). Most heat pumps are installed in regions with mild climates, such as the South Atlantic and Pacific regions, which is in line with the physics of heat pumps. In extremely cold areas, heat pumps' performance is lower, and the operating costs are higher. Electricity and natural gas prices come next in terms of correlation with heat pump adoption. Income is the third most important factor. Population density and environmental awareness level are not significantly correlated with heat pump adoption.

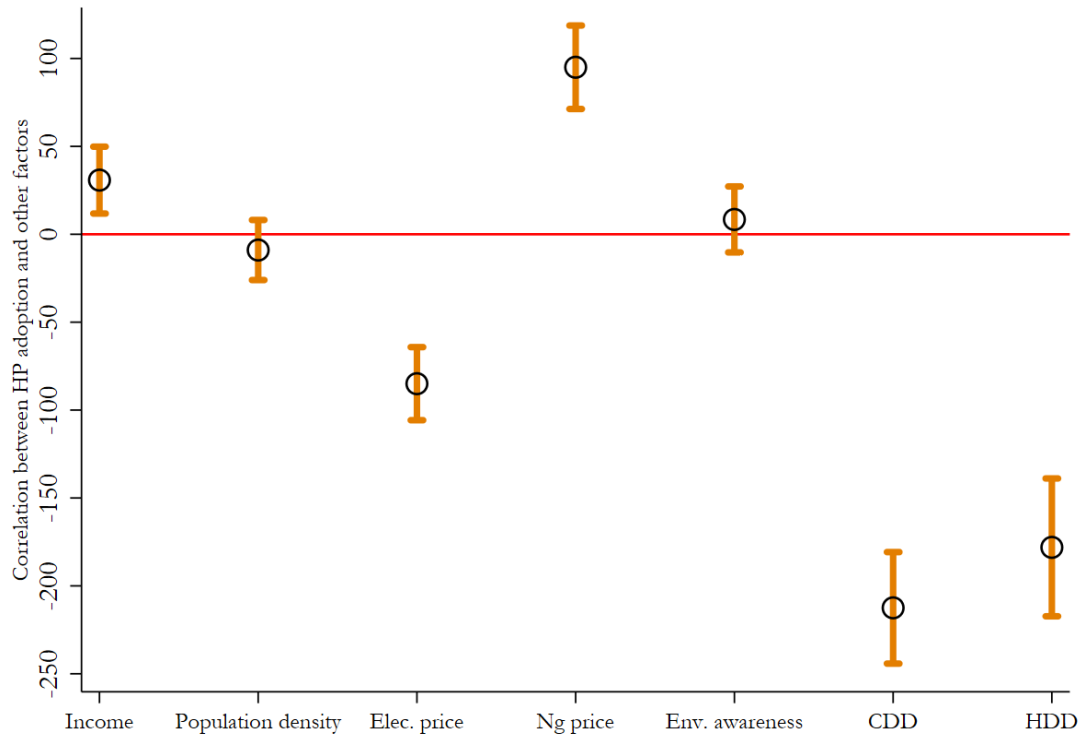


Figure 2.2 The correlation between heat pump adoption density (number of heat pumps per 10K persons) and other key factors.

Note: In the figure, circles are point estimates, and error bars are 95% confidence intervals. Here, I use U.S. national county-level data to regress the heat pump adoption density in 2018 on other variables including personal income per capita in 2016, population density in 2016, average residential electricity price in 2018 (Elec. price in the figure), average residential natural gas price in 2018 (Ng price in the figure), environmental awareness level in 2015 (Env. awareness in the figure), average annual heating degree days (HDD) and cooling degree days (CDD) from 1981 to 2010. I use the percentage of people who believe global warming is happening in a county to represent the level of environmental awareness. I standardize the independent variables into variables with 0 mean and 1 standard deviation. I obtain the data from the ZTRAX database, Bureau of Economic Analysis, U.S. Department of Commerce, U.S. Energy Information Administration, Yale Program on Climate Change Communication (Howe et al., 2015), and National Oceanic and Atmospheric Administration.

My analyses suggest that economic benefits may play a vital role in people’s decisions about heat pumps adoption. Price-based or other economic incentives can potentially influence the adoption density. Rebate and loan programs are the two most widely-used incentives. In North Carolina, the rebate amount for each newly installed heat pump provided by utilities ranges from \$200 to \$500. My study investigates the effect of a rebate program provided by the Duke Energy

utility. On Oct. 1, 2017, the Duke Energy utility introduced the rebate program to encourage the adoption of heat pumps. This program is available to all Duke Energy residential electric service customers. Eligible consumers should contact a qualified participating contractor (among the list provided by the Duke Energy utility) to conduct the work of installation. After completing the installation, the contractor will submit a rebate application on the consumer's behalf. The consumer will receive the rebate within 4-6 weeks. Consumers can look for a qualified contractor via the website of Duke Energy. The total rebate amount ranges from \$300 to \$450 depending on equipment efficiency. An air source heat pump with 15 and 16 Seasonal Energy Efficiency Ratio (SEER) is qualified for a \$300 rebate, and an air source heat pump with more than 17 SEER is qualified for a \$400 rebate. Also, if a smart thermostat is installed along with the heat pump, the consumer can obtain an additional \$50 rebate. Many utilities also offer a low-interest loan program for heat pump adoption. The interest rates of the utilities' loan programs range from 3.9% to 9% in North Carolina. According to the 2019 U.S. Federal Reserve data, the average personal loan interest rate and credit card interest rate from commercial banks are 10.32% and 15.05%, respectively (U.S. Federal Reserve, 2019). Thus, the interest rates provided by the utilities for heat pumps are relatively low. Moreover, the maximum amount of money that can be borrowed from these programs ranges from \$5,000 to \$10,000, which is enough to cover the average price of air-source heat pumps. The repayment period of these loan programs is usually 60 months. In my study, I compare the effect of the rebate with those of two loan programs (APR: 9%, 3.9%) provided by the Union Power utility and the Haywood utility.

3. A stylized model of energy efficiency investment under the rebate and loan incentives

In this section, I set up a stylized model to help understand the individual's decision on energy efficiency technology (e.g., heat pumps) adoption under the influences of rebate and loan programs. I analyze the decision process and compare the different effects of the rebate and loan when the consumers have and have no credit constraints.

When consumers face credit constraints, the loan program can have a significantly larger effect than the rebate program to promote energy efficiency investment. Loan programs can directly address the credit constraint issue, while the rebate program cannot solve the problem because the amount of rebate is usually a small part of the price of the energy efficiency technology. For example, if a heat pump costs \$8000 and the consumer only has \$2000 in savings, a rebate of \$500 will not be able to help the consumer install the heat pump, while a low-interest loan program will enable the consumer to borrow the remaining \$6000 and to be able to install the heat pump.

When there are no credit constraints, I set up the following stylized model following Berkouwer & Dean (2020) and Allcott & Greenstone (2012) to compare the different effects of rebates and low-interest loans. Agents have access to credits (borrow enough money) to purchase an energy efficiency good but need to make a series of repayments in the future. The energy efficiency adoption brings a series of benefits (such as energy fuel cost savings) in the future. A rational and time-consistent agent will adopt an energy efficiency good if and only if the current adoption costs are smaller than the present value of the future benefits of the adoption (Berkouwer & Dean, 2020):

$$u(P_e - b) < \sum_{t=1}^T (1 + \delta)^{-t} [u(\sigma_t - \tau_t)] \quad \dots (1)$$

where $u(\cdot)$ is the utility function; P_e is the price or upfront cost of an energy efficiency good (heat pump); b is the amount of money borrowed from the lender; δ is the individual's discount rate in terms of how to value future gains; σ_t is the fuel cost savings relative to a traditional inefficient system at time t ; τ_t is the repayment of the loan at time t . T is the lifetime of using the energy efficiency product. The equation between the amount of the principal/loan and the repayments is

$$b = \sum_{t=1}^T (1+r)^{-t} \tau_t \quad \dots (2)$$

where r is the interest rate of the loan. When the energy efficiency good's price makes the agent's utility indifferent between adopting and not adopting the good, the price is the agent's maximum willingness to pay (WTP). Here I assume a linear utility function and the maximum WTP for the energy efficiency good can be given by:

$$P^* = b + \sum_{t=1}^T (1+\delta)^{-t} \cdot (\sigma_t - \tau_t) \quad \dots (3)$$

Under the baseline situation with $\delta = r$, the maximum WTP in the above equation is equal to the discounted fuel cost savings, which is given by:

$$P^* = \sum_{t=1}^T (1+\delta)^{-t} \sigma_t \quad \dots (4)$$

Under the rebate incentive, agents receive an amount of cash and the down-payment for the energy efficiency good can be directly decreased, so the maximum WTP is increased to:

$$P^* + \Delta P = \sum_{t=1}^T (1+\delta)^{-t} \sigma_t + R \quad \dots (5)$$

where R is the amount of rebate. Under the incentive of a low-interest loan with $r < \delta$, the maximum WTP is increased to:

$$P^* + \Delta P = \sum_{t=1}^T (1 + \delta)^{-t} \sigma_t + \theta \cdot \left[\sum_{t=1}^T (1 + r)^{-t} \tau_t - \sum_{t=1}^T (1 + \delta)^{-t} \tau_t \right] \quad \dots (6)$$

When the interest rate is lower than the discount rate, the loan program provides subsidies for consumers. However, some consumers may be inattentive to this subsidy because it is complex and difficult to compute the present value of the subsidies (Grubb, 2015; Sexton, 2015). I use the coefficient θ to represent consumers' inattention and $0 \leq \theta \leq 1$. Based on the above model setup, the effects of the rebate and low-interest loan programs are equivalent when

$$R = \theta \cdot \left[\sum_{t=1}^T (1 + r)^{-t} \tau_t - \sum_{t=1}^T (1 + \delta)^{-t} \tau_t \right] \quad \dots (7)$$

The rebate is more effective in promoting heat pump adoption than the low-interest loan when

$$R > \theta \cdot \left[\sum_{t=1}^T (1 + r)^{-t} \tau_t - \sum_{t=1}^T (1 + \delta)^{-t} \tau_t \right] \quad \dots (8)$$

and the rebate is less effective otherwise.

Therefore, under the situation of credit constraints, providing access to credits in the loan program should be more effective. Without credit constraints, in theory, both rebate and loan incentives can help increase the adoption of heat pumps, but the relative magnitude of the impact depends on the amount of rebate, interest rate, consumers' discount rate, and consumers' inattention. In the following sections, I estimate the impact of rebate incentive on heat pump adoption and investigate which incentive (between the rebate and the loan) is more effective based on empirical evidence in North Carolina.

4. Data and empirical strategy

4.1 ZTRAX Data

I obtain the residential building characteristics data from the ZTRAX database (Zillow's Assessor and Real Estate Database) provided by Zillow Group. The ZTRAX data covers more than 150 million homes in over 3,100 counties and 51 states of the U.S. I can observe the building characteristics at the individual building level from the ZTRAX dataset via eight independent assessments⁶ from 3/22/2016 to 01/02/2020, which form a panel dataset. Local Town/County tax assessment offices conducted these assessments to evaluate property tax. The building characteristics information in the dataset includes geographical addresses, year built, year remodeled, space heating and cooling systems, number of stories/total rooms/bedrooms/bathrooms, lot size, building area, land assessed value, building condition, site/view characteristics, swimming pool, among many others. These building characteristics are updated after each assessment and include time-varying characteristic variables. The ZTRAX database has been widely used and validated by many studies (Bernstein et al., 2019; Baldauf et al., 2020; Buchanan et al., 2020; Boslett & Hill, 2019; D'Lima & Schultz, 2020; Nolte, 2020; Onda et al., 2020; Clarke & Freedman, 2019). My study focuses on the part of North Carolina of the dataset, which includes all the privately owned residential properties.

4.2 Supporting Data

⁶ The ZTRAX dataset records eight independent assessments on 3/22/2016, 02/03/2017, 07/31/2017, 11/02/2017, 01/07/2018, 08/05/2018, 12/30/2018, 01/02/2020.

Other supporting data were obtained from different open data sources. The personal income per capita, population density, age, household income, education level, and gender ratio data are sourced from United States Census Bureau's American Community Survey 1-year Estimates, reported at the Census Block Group level, for the release year 2016. The average residential electricity and natural gas prices data at the state level in 2018 were obtained from the website of the U.S. Energy Information Administration⁷. The local residents' environmental awareness level data was obtained from the Yale Program on Climate Change Communication (Howe et al., 2015). The heating and cooling degree days data at the county level were obtained from the "Climate Data Online" database of the National Oceanic and Atmospheric Administration.

4.3 Empirical methodology

Utility companies provide different incentives for residential heat pumps, including rebate and low-interest loans (see the distribution of all the electric utilities in North Carolina in **Appendix C**). Leveraging the geographical variation of incentives for heat pumps provided by different utilities, I estimate the effect of a rebate program on heat-pump adoption and compare the effect of the rebate with those of two loan programs via three different quasi-natural experimental approaches.

There are two common challenges when estimating the average treatment effect on treated (ATT). The first challenge is selection bias (Angrist and Pischke, 2008). I cannot directly observe the behaviors of consumers if they had not been influenced by the policy using observational data. Traditional cross-sectional analysis usually uses consumers' behavior in a control group (where

⁷ I obtained the state-level natural gas prices and electricity prices from the two websites: https://www.eia.gov/dnav/ng/ng_pri_sum_a_EPG0_PRS_DMcf_m.htm; <https://www.eia.gov/electricity/data/state/>.

the policy is not in place) as a counterfactual. However, if the household characteristics and behavioral patterns are significantly different between the treatment and control groups, the behavior of consumers who had access to the incentive policy if the incentive had not been in place might be different from the behavior of consumers in the control group, which leads to potential selection bias. The second challenge is omitted variable bias. The assignment to the treatment (e.g., the incentive policies) may be correlated with unobservable variables which also affect the outcome variable of my interest, leading to an endogenous estimation bias (Imbens, 2004; Abbott and Klaiber, 2011). For instance, residents located in various utilities may also have different unobserved characteristics such as different levels of environmental awareness which may directly influence their preference for the adoption of energy-efficient appliances.

To address the above concerns, I examine a narrow buffer zone along the borderlines between the Duke Energy Corporation and three other electric utilities with different incentives (or without incentives). The borderline is chosen to avoid overlap with administrative boundaries (e.g., state, county, township, etc.) and must be within the same ZIP code areas, to avoid any differences caused by different locations and administrations. The Duke Energy utility provides a rebate program for all kinds of space heating heat pumps⁸ and is adjacent to three other utilities (Rutherford Electric Membership Cooperative (EMC), Union Power EMC, and Haywood EMC). Among the three neighboring utilities, Rutherford EMC provides no incentives, Union Power EMC provides a loan program with 9% of APR, and Haywood EMC provides a loan program with 3.9% of APR for encouraging all kinds of space heating heat pump installations⁹, which can serve as three control or comparison groups, respectively (See **figure 2.3** for the illustration of research

⁸ The rebate program covers the installations of all kinds of heat pumps for space heating (including air source heat pumps, geothermal heat pumps, central heat pumps, mini-split heat pumps, etc.).

⁹ It includes air source heat pumps, geothermal heat pumps, central heat pumps, mini-split heat pumps, etc.

design). By obtaining local samples based on the three borderlines, I am able to estimate the effect of the rebate and also compare it with those of two loan programs.

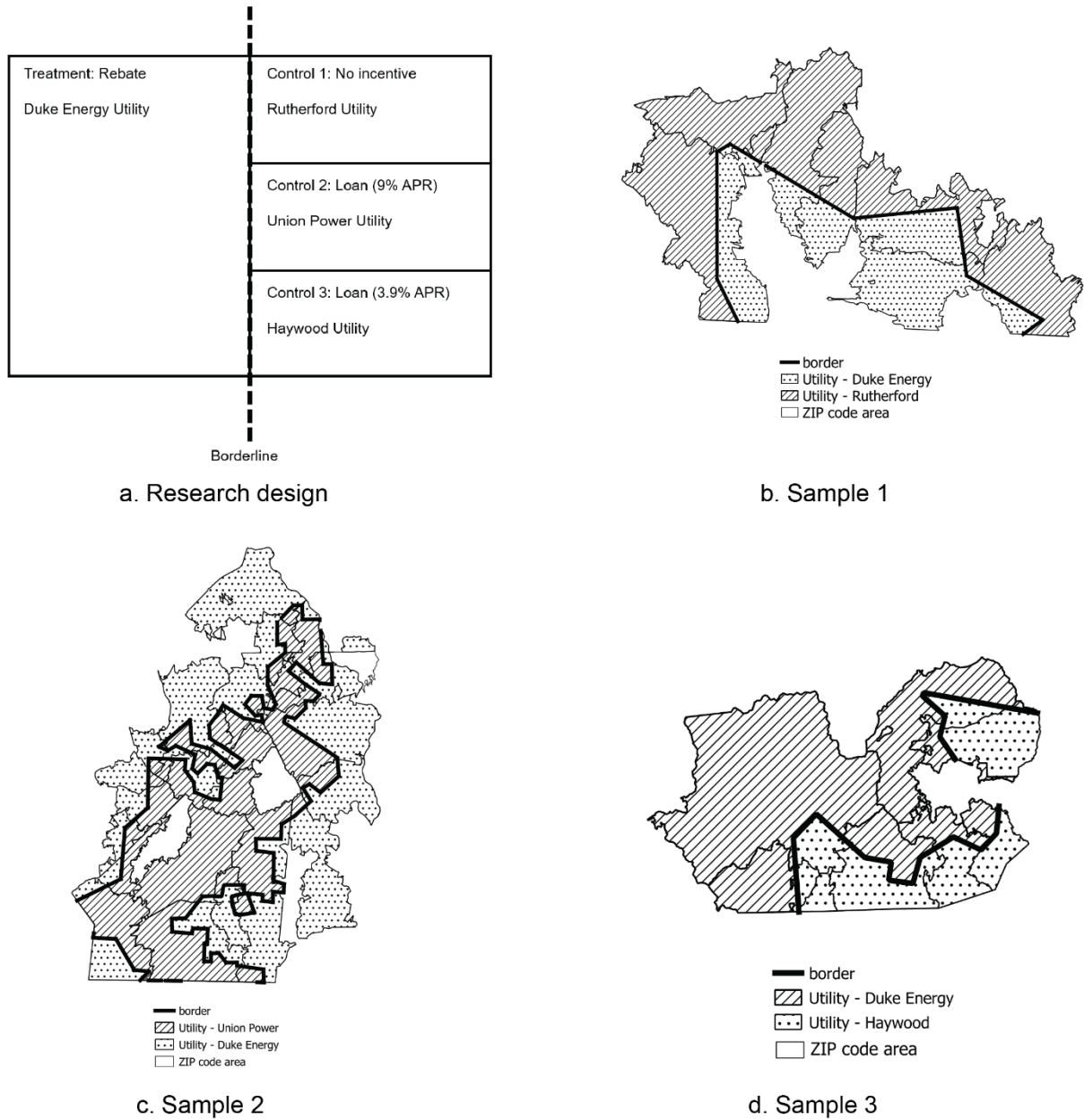


Figure 2.3 The research design and sampling distributions

My sample restrictions follow two rules simultaneously. First, households should be within the same ZIP code areas along the borderline. Second, I only include households within 3 miles of

the borderline as my final sample. Sample 1 is a rural area, located to the west of the Charlotte metropolitan area. It covers the following cities and towns: Rutherfordton, Forest City, Ellenboro, Shelby, Kings Mountain, and others. Sample 2 is a suburban area, which is in the east of the Charlotte metropolitan area. It covers east of Charlotte City, Mint Hill, Matthews, Monroe, Fairview, Concord, and others. Sample 3 is a rural area near the Nantahala National Forest, located to the west of Sample 1 and to the south of Great Smoky Mountains National Park. It covers the following cities and towns: Highlands, Franklin, Webster, Sylva, and others.

Sampling within a very narrow geographic region alleviates the concerns for potential confounding factors (e.g., environmental awareness level, education level, income, population density, urban/rural, and climate) that may lead to selection bias and omitted variable bias, given the hypothesis that the observable and unobservable attributes of neighboring households, living in a narrow region, should be comparable (Ito, 2014).

Table 2.1 presents a balance check based on observable covariates along the three borderlines¹⁰. I compare the building characteristics and demographic features of households within 3 miles of the borderline between the treatment and control groups, using the ZTRAX 2020 assessment data and the US Census Bureau's American Community Survey 1-year Estimates in 2016¹¹. I use two balancing statistics including standardized mean difference (SMD) and variance ratio (VR), to check the balance (Linden and Samuels, 2013). The SMD is used for comparing the sample mean and VR is used for comparing distribution, both of which have been widely used in

¹⁰ The average population density of counties covered by sample 1, sample 2, and sample 3 are 229, 800, and 75 persons per square miles, respectively. The average annual CDD and HDD of counties covered by sample 1 are 2193 and 2621. The average annual CDD and HDD of counties covered by sample 2 are 2482 and 2402. The average annual CDD and HDD of counties covered by sample 3 are 1384 and 3287. The data of population density, HDD, and CDD at the county level are from Bureau of Economic Analysis, U.S. Department of Commerce, and National Oceanic and Atmospheric Administration.

¹¹ The building characteristics obtained from the ZTRAX database is at the individual building level, while the demographic features obtained from the US census data are at the census block group level. I use the averages at the census block group level to approximate each individual household's demographic features.

statistic research (Stuart et al., 2013). According to Rubin (2001), if SMD is smaller than 0.25 and VR is in the range between 0.5 and 2, the treatment and control groups are balanced for this covariate in terms of mean and distribution. The first sample is well balanced on building characteristics, while some of the demographic features, such as age, income, and gender ratio, are not strictly balanced. My second sample (Duke Energy vs. Union Power) is perfectly balanced on the observable building characteristics (e.g., building condition, building age, number of rooms, etc.) and demographic features (e.g., age, income, education, etc.). My third sample (Duke Energy vs. Haywood) is in general well balanced on both observable building characteristics and demographic features except for two covariates (population median age and building's year remodeled¹², which I control for in one of my robustness checks).

¹² Although these two covariates are not strictly balanced according to Rubin's criterion (2001), the differences in terms of these covariates are not big. The population median age is 4 years older and the buildings' average year remodeled is 7 years older on the side of Haywood utility than on the side of Duke Energy utility. All the other covariates are strictly balanced. Thus, sample 3 is overall balanced.

Table 2.1 Covariates balance check: Comparing households (within 3 miles of borderlines and within the same ZIP code areas) in two utilities

	Mean	Std. Dev.	Mean	Std. Dev.	SMD	VR
Panel A: Sample 1	Duke Energy		Rutherford			
	(n=15,040)		(n=16,521)			
Building Characteristics:						
Building condition	4.23	1.00	4.44	1.00	0.21	1.00
Year built	1969	25.50	1975	24.40	0.24	1.09
Year remodeled	1983	12.80	1986	12.90	0.23	0.98
N. of stories	1.09	0.27	1.10	0.30	0.04	0.81
N. of bedrooms	2.89	0.77	2.93	0.70	0.05	1.21
N. of bathrooms	1.72	0.87	1.92	0.80	0.24	1.18
Census Characteristics:						
Median age	43.70	7.30	46.20	4.60	0.41	2.52
Median household income	37580	9044	43632	11065	0.60	0.67
Per capita income	21339	6633	23855	6313	0.39	1.10
male/female	0.87	0.21	0.95	0.15	0.44	1.96
Share of high school degree	0.28	0.08	0.27	0.06	0.14	1.78
Share of bachelor degree	0.11	0.07	0.12	0.06	0.15	1.36
Share of master degree	0.05	0.04	0.05	0.03	0.00	1.78
Share of doctor degree	0.01	0.01	0.01	0.01	0.10	1.00
Share of households with earnings	0.66	0.10	0.71	0.09	0.53	1.23
Panel B: Sample 2	Duke Energy		Union Power			
	(n=58,437)		(n=49,156)			
Building Characteristics:						
Building condition	4	0.35	4	0.32	0.00	1.20
Year built	1989	19.6	1987	22.4	0.10	0.77
Year remodeled	1991	10.5	1988	10.9	0.28	0.93
N. of stories	1.49	0.5	1.43	0.49	0.12	1.04
N. of bedrooms	3.3	0.77	3.4	0.85	0.12	0.82
N. of bathrooms	2.3	0.75	2.3	0.82	0.00	0.84
Census Characteristics:						
Median age	39	6.92	40.7	6.67	0.25	1.08
Median household income	73686	32621	75493	35237	0.05	0.86
Per capita income	29947	11620	32271	12836	0.19	0.82
male/female	0.96	0.14	0.98	0.15	0.14	0.87
Share of high school degree	0.21	0.09	0.22	0.1	0.11	0.81
Share of bachelor degree	0.24	0.12	0.24	0.13	0.00	0.85
Share of master degree	0.08	0.06	0.07	0.05	0.18	1.44
Share of doctor degree	0.009	0.01	0.01	0.01	0.10	1.00
Share of households with earnings	0.84	0.09	0.83	0.08	0.12	1.27

Table 2.1: Continued

	Mean	Std. Dev.	Mean	Std. Dev.	SMD	VR
Panel C: Sample 3						
	Duke Energy (n=15,709)		Haywood (n=7,808)			
Building Characteristics:						
Year built	1981	19.9	1980	21.4	0.05	0.86
Year remodeled	1980	12.1	1987	12.9	0.56	0.88
N. of stories	1.13	0.29	1.16	0.31	0.10	0.88
N. of bedrooms	2.83	0.89	2.8	0.91	0.03	0.96
N. of bathrooms	2.34	1.1	2.38	1.12	0.04	0.96
Census Characteristics:						
Median age	50.33	9.06	54.38	5.48	0.54	2.73
Median household income	48369	10724	46312	9431	0.20	1.29
Per capita income	31729	11964	34865	11904	0.26	1.01
male/female	0.93	0.19	0.95	0.12	0.13	2.51
Share of high school degree	0.2	0.09	0.21	0.08	0.12	1.27
Share of bachelor degree	0.19	0.075	0.2	0.07	0.14	1.15
Share of master degree	0.07	0.037	0.07	0.034	0.00	1.18
Share of doctor degree	0.01	0.018	0.01	0.01	0.00	3.24
Share of households with earnings	0.64	0.088	0.65	0.055	0.14	2.56

Note: I use two balancing statistics (standardized mean difference (SMD) and variance ratio (VR)) to check the balance between the control group and treatment group (Linden and Samuels, 2013). According to Rubin (2001), if SMD is smaller than 0.25 and VR is in the range between 0.5 and 2, the treatment and control groups are balanced for this covariate in terms of sample means and distribution. I obtained the individual building characteristics data from the ZTRAX database and obtained the demographic characteristics at the census block group level from the US census data based on the 2016 American Community Survey. As for the covariate of building conditions, the ZTRAX database records six levels of building conditions for each property, which are “Unsound”, “Poor”, “Fair”, “Average”, “Good”, “Excellent.” I transform the building condition variable into an ordinal variable with six integers from 1 to 6. A more stable, newer, and sounder building at the time of assessment implies a higher building condition recording.

For the first sample, I apply two approaches, namely DID and spatial RD, to estimate the effect of the rebate on heat-pump adoption, respectively. Although the first sample is not as balanced as the other two samples, the DID and RD approaches do not require strictly balanced covariates. I show that the pre-treatment parallel trend test in the DID design is passed in the first sample in the later section. In my research design, the first sample provides the intention-to-treat estimates. For the second and third samples, I estimate the difference in differential trends of heat

pump adoption to directly compare the effect of the rebate with those of the other two loan programs. Econometric model details are illustrated in the following sections.

I specifically select the buffer areas of the four utilities as my samples for the following reasons. To estimate a causal impact of the rebate with the DID method, I identify a utility area with only one rebate incentive for heat pumps and a neighboring utility area without any incentives for heat pumps. The buffer area between the Duke Energy utility and the Rutherford utility area is the only qualified area I can find in North Carolina. Similarly, to make a robust comparison between Duke Energy's rebate and other loan programs, I have to find a buffer area between the Duke Energy utility and another neighboring utility area with only one loan program for heat pumps. Many utilities provide both rebate and loan programs for heat pumps, which are not qualified for my study. The Union Power utility and the Haywood utility are two of the few areas that only provide one loan incentive for heat pumps and are also adjacent to the Duke Energy utility.

4.3.1 Difference-in-differences

I first apply the DID method to estimate the effect of the rebate on air-source heat pump adoption based on the borderline between the Duke Energy utility and the Rutherford utility. The Duke Energy utility starts to provide a cash rebate (\$300-\$450) for residential heat-pump adoption on 10/01/2017 (see the heat adoption rate before and after the rebate policy in sample 1 in **Appendix D**), while the Rutherford utility does not have any incentives for heat pumps, which enables a DID specification along the borderline. The DID approach controls for time-invariant confounding factors. For instance, the two electricity utilities had different residential electricity prices leading to different fuel costs using heat pumps. This electricity price gap may influence

heat pump adoption. My study chooses a time window with time-invariant residential electricity prices for both utilities in the first sample to rule out this confounder. My narrow sampling also helps control for time-variant confounding factors in the DID setting. First, the narrow sampling controls for potential differential impacts of natural gas price, which influences the energy bill savings associated with a switch from natural gas furnaces to heat pumps. The sample included in my study is within the same natural gas utility and both treatment and control groups face the same natural gas price. Second, in the DID specification, I show that the narrow spatial buffer helps justify the assumption of parallel trends between the treatment and control groups if the treatment had not been in place.

I apply the following two-way fixed effects model (a generalized DID model) using observations in both the pre-treatment and post-treatment periods (including 2016-3-22, 2017-2-3, 2017-7-31, 2017-11-2, 2018-1-7, 2018-8-5, and 2018-12-30):

$$Y_{it} = \beta D_{it} + \varphi_i + \sigma_z \cdot \vartheta_t + \varepsilon_{it} \quad \dots (9)$$

where Y_{it} is the outcome of interest. I apply two forms of outcome variables to measure the heat pump adoption at two levels: (1) a binary variable at the individual level indicating whether household i installs a heat pump in time t ; (2) a continuous variable at the 500m×500m geographical grid level measuring the residential heat-pump installation rate within the grid i and in time t , calculated by the share of households with the installation of heat pumps. The 500m×500m geographical square grids were artificially plotted on the map by the researchers. D_{it} is the treatment variable, which takes value one for household i (or, 500m*500m grid i) in the Duke Energy utility after the implementation of the rebate program and zero otherwise. φ_i is the

individual household (or grid) fixed effects. $\sigma_z \cdot \vartheta_t$ is the ZIP-code-by-year fixed effects or the income-intervals-by-year fixed effects. I divide the household income into four quartiles. ε_{it} is the error term. According to the balancing tests (See the Panel A of **Table 2.1**), the household income between treatment and control groups is not strictly balanced in the first sample. Also, the income has a statistically significant correlation with heat pump adoption based on my national exploratory analysis in section 2, which may confound my DID estimation. Although I pass the pre-treatment parallel trend test (See section 5), I include income-intervals-by-year fixed effects in the model for robustness to allow differential trends across the income intervals to rule out the confounder of income.

When I use the binary variable as the outcome in my DID specification, I am estimating a linear probability model (LPM) in conjunction with the DID. The LPM-DID models have been widely used by many economic studies to evaluate the impacts of market reforms (Buchmueller and DiNardo, 2002; Monheit and Schone, 2004; Levine, McKnight, and Heep, 2011; Monheit et al. 2011). Compared to non-linear DID models (e.g., logit or probit DID models), the LPM-DID model has advantages: (1) the LPM-DID directly estimates the impact of a relevant policy and the coefficient can be easily interpreted as “percentage point changes in coverage outcomes” (Cantor et al., 2012); (2) the LPM-DID avoids the complications in estimation and interpretation of “multiple interaction terms and their standard errors in the logit or probit models” (Cantor et al., 2012; Ai and Norton, 2003). Nevertheless, the LPM-DID model also has disadvantages. It is not well suitable for outcomes with highly skewed values with high zero mass since it may violate Ordinary Least Squares (OLS) regression’s assumptions, such as normally distributed errors and homoscedasticity (Wooldridge, 2010). For robustness, I apply an alternative continuous outcome

variable measuring the residential heat-pump installation rate at the 500m×500m geographical grid level.

4.3.2 Spatial regression discontinuity

I further combine the DID approach with the spatial RD method to estimate the local effect of the rebate on heat-pump adoption at the borderline based on the first sample. RD has been widely used by empirical studies to evaluate policy impacts by comparing the differences in the outcome around the cutoff. Subjects receive the treatment on one side of the cutoff while receiving no treatment on the other side of the cutoff. Since subjects at the cutoff share the same probability of receiving the treatment, RD approximates a natural experiment at the cutoff region. In my study, I follow two steps to estimate the rebate effect using the DID-RD approach and only use the variables at the individual household level. First, I compute the first difference of the dependent variable, namely the dummy variable indicating heat pump adoption status for each household. Second, using the computed first differences as the outcome, a local linear regression discontinuity model is applied to estimate the local average treatment effect (LATE) of the rebate on heat-pump adoption. Intuitively, I compare the changes in heat-pump adoption statuses of households who are infinitely close to one side of the border with those of households who are infinitely close to the other side of the border. Although the RD-DID estimator is more local, it has an advantage. Treatment and control groups at the cutoff should be indifferent except for the treatment status, so there should be no differential trends of heat pump adoption at the cutoff between the treatment and control groups if the treatment had not been in place. The parallel trend assumption of the DID is met at the cutoff. The time window in the RD-DID analysis is from 03/22/2016 to 08/05/2018.

A local linear regression with a triangular kernel function, which has been a standard choice for RD estimations (Imbens and Lemieux, 2008; Lee and Lemieux, 2010), is applied as follows:

$$\Delta Y_{i,t_1,t_2} = \alpha + \beta D_i + \gamma(X_i - c) + \delta D_i(X_i - c) + \varepsilon_i \quad \dots (10)$$

where $\Delta Y_{i,t_1,t_2}$ is the first difference of a binary variable indicating whether household i installs a heat pump in time t . D_i is a binary treatment group variable, which equals to one if household i is located in the Duke Energy utility and if $X_i \geq c$. X_i is the running variable, measuring the distance to the borderline of household i . When household i is in the Duke Energy utility (treatment group), $X_i > 0$; when household i is in the Rutherford utility (control group), $X_i < 0$. c is the treatment cut off, which equals zero. ε_i is the error term. A triangular kernel function on the distance of each household to the borderline is applied to compute the weights when approximating the regression functions below and above the cutoff (Calonico et al., 2014). Since the performance of point estimators and confidence intervals in RD is sensitive to the specific bandwidth selected, I use the mean squared error (MSE)-optimal approach (Imbens and Kalyanaraman, 2012) to compute a data-driven bandwidth for the RD point estimator. However, the MSE-optimal bandwidth selector usually leads the confidence interval inferences biased (Calonico et al., 2014). To ensure robust confidence intervals, I use the robust bias-corrected (RBC) methods (Calonico et al., 2014, 2020) to compute the bandwidth for confidence interval inference. The β is the coefficient of my interest, which measures the local average treatment effect of the rebate program on heat pump adoption.

4.3.3 Difference in differential trends in conjunction with spatial discontinuity

For the second and third samples, I compute the difference in differential trends in conjunction with spatial discontinuity to estimate the relative effects of Duke Energy’s rebate program over the other two loan programs (with 9% and 3.9% of APR), respectively. I examine the borderlines between the Duke Energy utility, with a rebate program, and the other two utilities with loan programs (Union Power EMC, and Haywood EMC). The Union Power EMC has provided access to loans (APR: 9%) for heat-pump adoption since 2006, while the Haywood EMC has provided the loan program (APR: 3.9%) for residential heat pumps since 2010. My panel data starts from 2016, so I cannot apply a standard DID specification since pre-treatment period (before the implementation of the loan programs) data are not available. I, therefore, compare the differential growth trends of the heat pump adoption rate along the borderlines between two utilities. I emphasize that the treatment (i.e., the rebate or loan incentive) is assigned in both pre- and post-periods when I am comparing the differential trends across the borderline, which is different from the typical DID specification. I choose a time period (from 11/02/2017 to 01/02/2020) when households on both sides of the borderlines had access to the incentives, while households received rebates on one side and received loans on the other side. Also, I focus on observations within the same ZIP code areas and within 3 miles of the borderlines.

Not all households need to install new heating systems in a given time. For most households (who live in old buildings) in the U.S., the decision to install a heat pump is made when they need to replace their old heating equipment (e.g., natural gas furnaces, electric resistance heating, and others). The installation of a heat pump is quite different from a solar panel, which is a completely new addition to households. Thus, only a fraction of households whose heating equipment is old or not functioning well, have the potential demand to replace their heating equipment with a new heat pump. Given the relatively small incentives studied in the paper, it is likely that the rebate and

loan programs can only alter the decisions of homeowners whose heating equipment is old or not functioning well at a specific time. The demand for replacing heating equipment is thus released every year when different sets of households need to replace their old units. Conditioning on the small buffer area and balanced observed attributes, we assume that the number and attributes of households, who have the demand for replacing heating equipment, are comparable across the two sides of the borderline at any specific time in our study period. Thus, I can compare the effects of the rebate and loan, although the loan programs in our study were introduced earlier than the rebate program. Nevertheless, I acknowledge that the loan's effect is a long-run effect and the rebate's effect is a short-run effect in my sample.

Studies comparing the effectiveness of different policies using the estimations coming from different sites could be problematic when the ATT varies with different treated groups or sites (Allcott, 2015). To avoid this issue, I focus on a narrow spatial buffer to exclude the site selection bias in program evaluations. Another potential concern is different electricity prices between the utilities, which may also influence the heat pump adoption. Unlike in the first study (sample) where I use DID to eliminate the influence of time-invariant prices, here I estimate the impact of electricity price on heat pump adoption density using a fixed-effects model with a North Carolina state-wide panel dataset. I find that the estimated effect of electricity price on heat pump adoption is minimal compared to the effects of rebate over loan (see detailed estimations in Section 5.3). Therefore, my major conclusion still holds since there is little effect of electricity price on the heat pump adoption in the second and third samples.

I apply the following two-way fixed effects model using observations in two periods (11/02/2017 and 01/02/2020) after the implementation of rebate and loan programs to estimate the difference in differential trends:

$$Y_{it} = \beta D_{it} + \varphi_i + \sigma_z \cdot \vartheta_t + \varepsilon_{it} \quad \dots (11)$$

where Y_{it} is the outcome variable. I take two forms of outcome: (1) a binary variable indicating whether household i installs the heat pump in time t ; (2) the residential heat-pump installation density (share of households with heat pumps) within a 500m×500m geographical grid i in time t . D_{it} is a dummy variable, which takes value one for households or grids in the Duke Energy utility and in the second period, and takes value zero otherwise. φ_i is the individual household (grid) fixed effects. $\sigma_z \cdot \vartheta_t$ is the ZIP-code-by-year fixed effects. ε_{it} is the error term. β is the coefficient of my interest, comparing the changes in heat pump adoption status (or rate) from the first to the second periods under the influence of the rebate with those under the influence of the loan. A positive β implies that the heat pump adoption growth rate is higher under the rebate compared to that under the loan and vice versa. Limited by the empirical context, I cannot isolate the effect of a loan program. The loan programs were started earlier than the beginning of the data period, and I cannot find qualified neighboring utilities without any incentives for residential heat pumps as control groups. Thus, I cannot apply a standard DID specification along a borderline to estimate a robust treatment effect of a loan program.

4.3.4 Summary of the research design

In the above section, I outline my empirical strategies comparing three specific incentives: a rebate (\$300-\$450) program by the Duke Energy utility, a loan program with 9% APR by the Union Power utility, and a loan program with 3.9% APR by the Haywood utility. The three incentives apply to all types of heat pumps for space heating (e.g., air-source heat pumps, ground-

source heat pumps, central heat pumps, ductless mini-split heat pumps, etc.), but I only estimate the incentives' effect on air-source heat pump adoption. Air source heat pump is the most common type of heat pump. The rebate amount I investigate is typical in North Carolina. The loan programs' interest rates I investigate can roughly cover the range of the interest rates for heat pumps provided by utilities in North Carolina. All the members within the Union Power and Haywood utilities are qualified to apply for the fixed low-interest loan programs. The maximum amount of money borrowed in the programs can cover the full costs of installing a typical air-source heat pump. I examined three borderlines between two utilities (Duke Energy – Rutherford; Duke Energy – Union Power; Duke Energy – Haywood). I analyze the samples of households within the same ZIP code and within 3 miles of the borderline. The first study uses the DID and DID-RD approaches to estimate the rebate effect. The second and third studies compare differential growth trends to estimate the relative effect of rebate over loan. **Table 2.2** summarizes the three studies and research designs. Research designs are guided by the sampling periods and the availability of an appropriate control group.

Table 2.2 Summary of studies using the three samples

Studies/Samples	Period 1	Period 2	Period 3	Aim and Method (in parentheses)
Utility 1: Duke Energy	No incentives	Rebate (\$300-\$450)		Rebate's effect (Difference-in-differences; Spatial regression discontinuity)
Utility 2: Rutherford EMC	No incentives	No incentives		
Utility 1: Duke Energy		Rebate (\$300-\$450)	Rebate (\$300-\$450)	Relative effect of rebate over loan (Comparing differential growth trends between the two utilities within a narrow buffer zone)
Utility 3: Union Power EMC		Loan (APR: 9%)	Loan (APR: 9%)	
Utility 1: Duke Energy		Rebate (\$300-\$450)	Rebate (\$300-\$450)	Relative effect of rebate over loan (Comparing differential growth trends between the two utilities within a narrow buffer zone)
Utility 4: Haywood EMC		Loan (APR: 3.9%)	Loan (APR: 3.9%)	

5. Results

5.1 The effect of the rebate program using DID

Table 2.3 presents the estimates of the effect of the rebate program by including different sets of fixed effects and using LPM-DID models and DID models. All the coefficients of the treatment variable in **Table 2.3** are significantly positive, showing that the rebate program can successfully encourage the heat-pump installation. Columns (2) and (5) present results from my preferred specifications, which include the ZIP-by-year fixed effects and better control for potential unobserved heterogeneity. The rebate program significantly increased the probability of installing a heat pump by 1.3% on average across the four post-treatment periods (or an 11% increase compared to the pre-treatment periods in the treatment group) and increased residential heat pump

adoption density (share of households with heat pumps within a 500m*500m grid) by 0.012 (or a 6.7% increase).

Table 2.3 The effect of rebate program on heat pump adoption using DID approach

Model	LPM-DID			DID		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Binary variable: adopting heat pump			Heat pump density within a 500m*500m grid		
1[Rebate]it	0.008*** (0.003)	0.013*** (0.003)	0.017*** (0.003)	0.01* (0.006)	0.012*** (0.004)	0.022*** (0.006)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
ZIP-by-Year FE	No	Yes	No	No	Yes	No
Income-by-Year FE	No	No	Yes	No	No	Yes
Overall Adjusted R2	0.1	0.19	0.06	0.11	0.16	0.08
Obs	220,915	220,915	220,915	22,729	22,729	22,729
Mean of outcome variable	0.22	0.22	0.22	0.24	0.24	0.24

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in the parentheses and clustered at the individual (household, or 500m*500m grid) level. “Income-by-Year FE” means income-intervals-by-year fixed effects. I divide the household income into four intervals based on its quartiles. I focus on the sample of households within 3 miles to the borderlines. The observations include seven periods of 2016-3-22, 2017-2-3, 2017-7-31, 2017-11-2, 2018-1-7, 2018-8-5, 2018-12-30.

To further explore the time-variant treatment effects of the rebate by different periods, I interact the treatment variable with four dummies indicating four post-treatment periods (including 2017-11-2, 2018-1-7, 2018-8-5, and 2018-12-30), respectively, in my baseline DID models. Estimation results are presented in **Table 2.4**. Results show that the rebate program did not have

significant treatment effects on the first two post-treatment periods (2017-11-2 and 2018-1-7), which could be due to that these two periods are too close to the initial date of the rebate program and the additional demand to replace spacing heating equipment in that time span is little. Moreover, I find that the treatment effects became significantly positive in the last two post-treatment periods (2018-8-5 and 2018-12-30), which are about one year after introducing the rebate program. Based on the estimation results in column (5), the rebate program increased the adoption rate by 0.024 in a one-year period after the rebate program is introduced, or a 13% of increase compared to the pre-treatment periods. If I assume the rebate is all passed through to consumers and the price of heat pumps falls by \$300 to \$450. The average price of a typical air source heat pump is \$8000. So, the price elasticity of demand for heat pumps is from 2.31 to 3.46, which means that the demand for heat pumps is quite elastic.

Table 2.4 The effect of rebate program on heat pump adoption by different periods

Model	LPM-DID			DID		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Binary variable: adopting heat pump			Heat pump density within a 500m*500m grid		
1[Rebate]it * T1	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)
1[Rebate]it * T2	0.0009 (0.001)	0.0009 (0.001)	0.001 (0.001)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)
1[Rebate]it * T3	0.0143 (0.016)	0.025*** (0.01)	0.033** (0.017)	0.023** (0.01)	0.024*** (0.008)	0.048*** (0.011)
1[Rebate]it * T4	0.0142 (0.016)	0.025*** (0.01)	0.033** (0.016)	0.022** (0.01)	0.024*** (0.008)	0.046*** (0.011)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
ZIP-by-Year FE	No	Yes	No	No	Yes	No
Income-by-Year FE	No	No	Yes	No	No	Yes
Overall Adjusted R2	0.1	0.19	0.05	0.1	0.25	0.08
Obs	220,915	220,915	220,915	22,729	22,729	22,729
Mean of outcome variable	0.21	0.21	0.21	0.24	0.24	0.24

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in the parentheses and clustered at the individual (household, or 500m*500m grid) level. I focus on the sample of households within 3 miles to the borderlines. The observations in the sample include periods of 2016-3-22, 2017-2-3, 2017-7-31, 2017-11-2, 2018-1-7, 2018-8-5, and 2018-12-30. T1, T2, T3, T4 are dummies indicating four post-treatment periods of 2017-11-2, 2018-1-7, 2018-8-5, and 2018-12-30.

Observations after 12/30/2018 are excluded due to electricity prices change. The residential electricity prices in both utilities did not vary during the time window (from 03/22/2016 to 12/30/2018). Moreover, both treatment and control groups share the same natural gas utility and face the same natural gas prices during the study window.

To justify the parallel trend assumption of the DID approach, I conduct an event study as a robustness check. By applying the following regression, I estimated the treatment effect by different periods (including pre-treatment and post-treatment periods).

$$Y_{it} = \sum_{m=k, m \neq -1}^M D_{it,k} \times \beta^k + \varphi_i + \sigma_z \cdot \vartheta_t + \varepsilon_{it} \quad \dots (12)$$

where Y_{it} is the residential heat-pump installation rate within the grid (500m*500m) i and in time t . $D_{it,k}$ are a set of dummy variables indicating the treatment status at different periods. k takes values from -3, -2, 0, 1, 2, 3, which indicated 6 observed periods in our sample (2016-3-22, 2017-2-3, 2017-11-2, 2018-1-7, 2018-8-5, and 2018-12-30). The dummy for $m = -1$ is omitted in the equation, so that the treatment effect is calculated relative to the -1 period (2017-7-31) right before the introduction of the rebate. φ_i is the individual grid fixed effects. $\sigma_z \cdot \vartheta_t$ is year fixed effects, or ZIP-code-by-year fixed effects, or income-intervals-by-year fixed effects. **Figure 2.4** plots the estimation results of the event study with different specifications (by adding different fixed effects). All the plots show that there are no differential trends in heat pump adoption density between the treatment and control groups prior to the launch of the rebate policy. The pre-treatment parallel trend test is passed, which supports the key parallel trend assumption required by my DID specification.

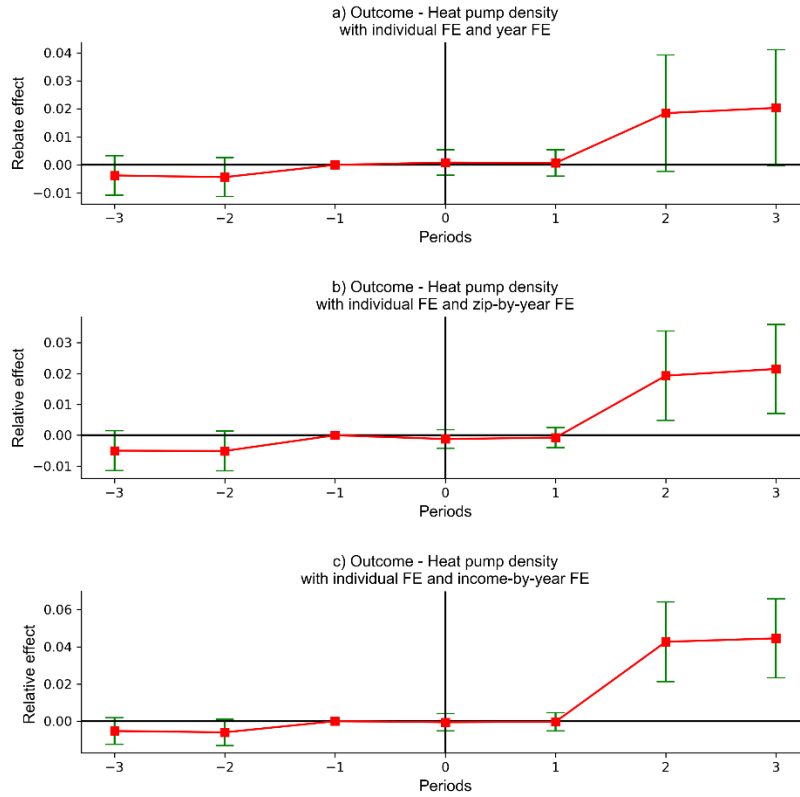


Figure 2.4 The event study of the rebate program for heat-pump adoption

Note: red points are point estimators, and green error bars are 95% confidence intervals. The seven periods are 2016-3-22, 2017-2-3, 2017-7-31, 2017-11-2, 2018-1-7, 2018-8-5, and 2018-12-30.

While the LPM model has been used in many other DID contexts, the decision to adopt a heat pump is effectively a one-time irreversible choice as opposed to repeated, non-permanent binary choices. For the setting of individual heat pump adoption, survival models can directly capture a data generating process that has a single event, although these survival models are nonlinear models that are not well suited for individual household fixed effects. I conduct a robustness check to estimate the rebate effect using a Cox proportional hazards model (See **Appendix E**). The Cox model shows a significant positive effect of the rebate, which is consistent with the LPM-DID model. The DID specifications that use adoption rates by grid can ameliorate the single-choice

problem, but the dependent variable could be censored with the possibility of increased development within the grid. I conduct an additional robustness check to address this potential problem. Using a Tobit model, I regress the first differences of heat pump adoption density on a dummy variable indicating the Duke Energy utility area. Estimates show positive effects consistent with my baseline estimations (See **Appendix F**).

5.2 The effect of the rebate program using DID-RD

I next combine the DID with the RD method to estimate the rebate effect. I compute the estimated treatment effect as the difference of the first differences of households' heat pump adoption status at the cutoff (borderline) for the treatment and control groups. First, I present graphical evidence for the rebate's effect. **Figure 2.5** shows the regression discontinuity plots with a polynomial regression function of order 3 and a local linear regression function, respectively. The polynomial order of 3 is chosen by the Bayesian information criterion¹³ (BIC). I use the integrated mean square error (IMSE)-optimal evenly spaced method (Calonico et al., 2015) to compute the number of bins (31 bins in plot *a* and 15 bins in plot *b*), which are assigned to calculate the sample averages within bins in both plots. The bandwidth is 5 miles in plot *a* and is 1 mile in plot *b*. Both plots demonstrate that the outcome variable (first differences in heat pump adoption status at the household level) jumps at the cutoff (borderline) and is higher at the side of the Duke Energy utility which implemented the rebate program, which provides suggestive evidence that the rebate program can increase the probability of installing a heat pump.

¹³ I regress the outcome variable (the first differences in heat pump adoption status) on the running variable using global polynomial specification allowing up to order 6. I compare the BIC of each model, and the model of polynomial order 3 is the best-fit model with the lowest BIC.

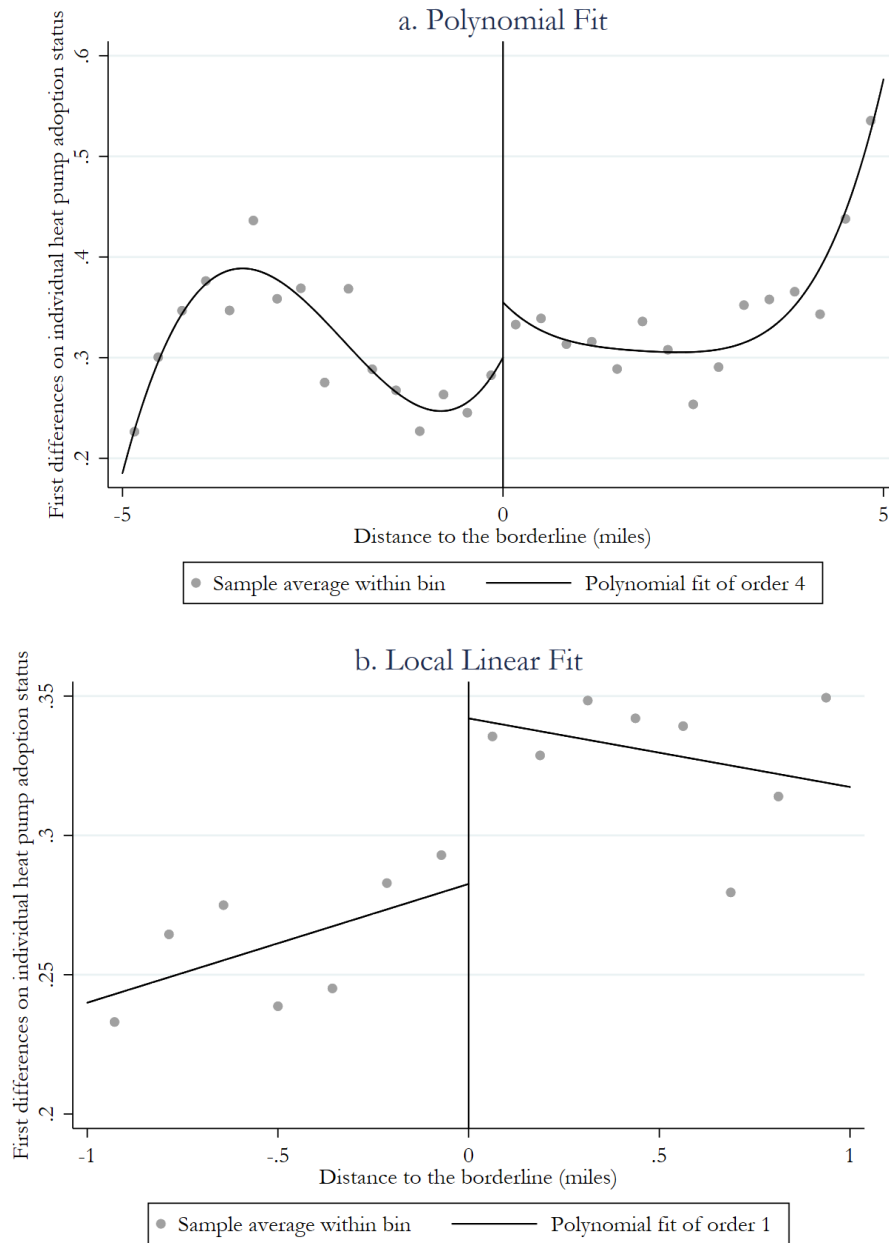


Figure 2.5 Regression discontinuity plots

Note: The distance to the borderline is above 0 at the side of Duke Energy utility and is less than 0 at the side of Rutherford utility

The bandwidths in the above RD plots are artificially set by researchers, which provides informal graphical evidence of the treatment effect. I then provide formal statistical evidence using a data-driven RD-DID approach. I utilize a nonparametric local polynomial estimator, which has been a standard choice for RD estimations (Imbens and Lemieux, 2008; Lee and Lemieux, 2010).

A local linear regression with a triangular kernel function is applied. I use the MSE-optimal approach (Imbens and Kalyanaraman, 2012) to compute the bandwidth employed for the RD point estimator, and a 0.867-miles bandwidth is chosen, leading to an effective sample size of 9,411 households. I use the robust bias-corrected (RBC) methods (Calonico et al., 2014, 2020) to compute the bandwidth for confidence interval inference and a 1.802-miles bandwidth is chosen. Results show that the estimated coefficient of β is 0.051, with a standard error of 0.025 and a p -value of 0.046. I reject the null hypothesis that there are no differences in heat pump adoption changes between the two utilities at the cutoff at a 95% confidence level. The rebate program can significantly increase the probability of installing a heat pump by 5.1% for households at the borderline. I conduct a McCrary (2008) manipulation test using local polynomial density estimation following Cattaneo et al. (2018)'s approach. The final test T statistic is 0.507, with a p -value of 0.61. There is no statistical evidence of systematic manipulation of the running variable (distance to the borderline) in my RD design. In addition, I conduct a robustness check using a traditional RD design by only including observations in the second period (See results in **Appendix G**).

5.3 The relative effect of the rebate program over loan programs

I use the second and third samples to estimate the relative effects of Duke Energy's rebate program over the two loan programs by comparing differential growth trends along the borderline within a narrow spatial buffer. I fit a regression model to compute the difference in differences in adoption rates across two periods on both sides of the borderline. Throughout the data window,

consumers had access to the rebate program on one side of the borderline and had access to the loan program on the other side of the borderline.

Table 2.5 presents estimates of the relative effects by including different sets of fixed effects and using different outcome variables. Columns (1) and (2) use the heat pump adoption status at the household level as the outcome variable, and Columns (3) and (4) use the heat pump adoption density as the outcome. The coefficients presented in the table measure the difference in heat pump adoption growth rates across the borderline of the two utilities with different incentives. Panel A in **Table 2.5** presents results on the relative effects of rebate over the loan program with 9% APR and panel B is for relative effects of rebate over the loan program with 3.9% APR. All the coefficients in **Table 2.5** are significantly positive, except for the coefficient in column (4) of panel A with zip-by-year fixed effects, indicating that the rebate program's effect on the adoption rate is larger than the two loan programs (9% and 3.9% APR).

My estimates are also economically significant. Based on the estimation in column (1), the rebate program can increase the likelihood of heat pump adoption by an additional 0.004 for a household in a two-year period, compared to the loan program with a 9% APR, suggesting that the rebate program can bring additional 233 heat pump installations in the Duke Energy service territory in a two-year period in our second sample. This second sample is overlapped with 3 counties (Cabarrus County, Mecklenburg County, Union County¹⁴). If I assume the rebate program was implemented by the three counties, the rebate program would bring additional 2,269 heat pump installations. The market value of 2,269 air source heat pumps is about 22 million US dollars using a back-of-the-envelope calculation. Similarly, based on the estimation in column (1), the rebate program can bring additional 581 heat pump installations in the Duke Energy service

¹⁴ The total number of households in the three counties (Cabarrus County, Mecklenburg County, Union County) is 567,324 based on U.S. Census American Community Survey 2019 one-year estimates.

territory in our third sample, compared to the loan program with a 3.9% APR. The third sample is overlapped with three counties (Jackson County, Macon County, Transylvania County¹⁵). The rebate program would bring additional 1,748 heat pump installations if the three counties implemented the rebate program. The market value of 1,748 air source heat pumps is about 17 million US dollars.

Although the treatment coefficients in panel B appear larger than those in panel A, the coefficients cannot be compared directly since the estimations are based on different samples. Therefore, the effectiveness of two loans program with different APRs cannot be compared directly in my samples.

Although the third sample is overall balanced, there are two imbalanced observable covariates, namely population median age and building's year remodeled. To fully rule out the potential influences of the two imbalanced covariates, I conduct a robustness test by directly controlling the covariates in my differential-trends model and find that my estimations are insensitive to adding the covariates. See detailed tests in **Appendix H**.

¹⁵ The total number of households in the three counties (Jackson County, Macon County, Transylvania County) is 47,221 based on U.S. Census American Community Survey 2019 one-year estimates.

Table 2.5 The relative effect of rebate over loan (APR:9%, 3.9%) by comparing differential trends

Model Outcome	(1) Binary	(2) Binary	(3) Density	(4) Density
Panel A: Rebate vs. Loan (9%)				
$1[Duke\ Energy]_{it}$	0.004*** (0.0004)	0.001** (0.0005)	0.0045*** (0.0013)	0.0006 (0.0014)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
ZIP-by-Year FE	No	Yes	No	Yes
Overall Adjusted R2	0.0011	0.0043	0.0033	0.096
Obs	214,728	214,728	13,970	13,970
Mean of outcome variable	0.11	0.11	0.14	0.14
Panel B: Rebate vs. Loan (3.9%)				
$1[Duke\ Energy]_{it}$	0.037*** (0.005)	0.039*** (0.005)	0.027*** (0.01)	0.028** (0.011)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
ZIP-by-Year FE	No	Yes	No	Yes
Overall Adjusted R2	0.04	0.06	0.092	0.006
Obs	47,034	47,034	2,502	2,502
Mean of outcome variable	0.15	0.15	0.14	0.14

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in the parentheses and clustered at the individual (household, or 500m*500m grid) level. I focus on the sample of households within 3 miles to the borderlines.

There are two other potential confounders in this research design: electricity price and natural gas price. First, according to the pre-treatment parallel trend test in the first study, there are no differential trends of heat pump adoption under two different time-invariant electricity prices, though the time-variant electricity price may still be a confounder in other contexts. In the second and third samples, the utilities of Union Power and Haywood did not change the residential electricity rate plan in my study window, but the Duke Energy utility decreased the marginal residential electricity price by about 0.5 cents on 01/01/2019, which might affect the heat pump

adoption trend. To address this concern, I show that the impact of changing electricity prices on heat pump adoption rate is negligible within North Carolina. Based on a panel data of 1 million residential buildings across 26 Electric Membership Cooperatives of North Carolina, I regress the heat pump adoption rate within a 1km×1km grid on the yearly average residential electricity prices of each cooperative controlling for individual grid fixed effects and year fixed effects using observations from 2016 to 2019. The heterogeneous incentives for heat pumps provided by different cooperatives can be captured by the individual grid fixed effects. I calculate the average residential electricity price by dividing the cooperative's residential total revenue by residential sales based on data from EIA 861 forms¹⁶. My estimate shows 0.5 cents decrease in residential electricity price leads to a 0.0008 increase in the heat pump adoption rate (See detailed estimation results in **Appendix I**). Thus, the impact of a decrease in electricity price in the Duke Energy utility is very small compared to my estimated effects of the incentives, and my main conclusion still holds. For the second concern, since both treatment and control groups share the same natural gas utilities, the natural gas price is controlled in my research design.

To sum up, I find that the rebate program (\$300-\$450) is more effective in promoting heat pump adoption than the other two loan programs (APR: 9%, 3.9%) under the assumption of comparable demand for replacing old heating equipment within the buffer area. This comparison is representative of North Carolina. The median household incomes in 2018 in the second and third samples are 74,534 and 47,675 US dollars. According to the 2018 U.S. census data, the median household income in North Carolina is 53,369 US dollars. Thus, my estimation is based on a sample that is comparable to average North Carolina consumers.

¹⁶Data source: U.S. Energy Information Administration, Annual Electric Power Industry Report, EIA 861 forms, <https://www.eia.gov/electricity/data/eia861/>

There are three potential explanations for my findings. First, most consumers' credit constraints are not binding given that the credit market is well-developed in the U.S. In addition to the utilities' loan programs, consumers may also have access to other loan programs in the U.S., such as personal loans provided by commercial banks, credit companies, etc. According to the 2019 U.S. Federal Reserve data, 26.1% of consumers have personal loans, and its average balance amount in North Carolina is \$16,359.89 which is much higher than the average price of air-source heat pumps (around \$8,000). Also, the average amount of household credit card debt in North Carolina is \$7,225 in 2018. (See the detailed personal loan and credit card data in the U.S. in **Appendix J**.) Thus, credit constraints should not be the primary hurdle for heat pump adoption in my sample. The major incentive of the utilities' loan programs comes from lower interest rates. Second, according to my stylized model, although under a certain condition the subsidies provided by the rebate program and the low-interest loan program can be equivalent, consumers may be inattentive to the subsidies caused by the lower interest rate. It is complex and difficult for some consumers to compare different interest rates and compute the present value of subsidies from the loan program. The cash rebate program can be more effective in increasing the WTP for heat pumps because it sends more straightforward information about the subsidies to consumers. The third possible reason is that consumers' perceived discount rate might be low. According to the stylized model in section 3, the incentive of the low-interest loan is related to the relative personal discount rate over the loan's interest rate. If a consumer's discount rate towards future cash flows is lower, the incentive effect of the low-interest loan is weaker.

6. Robust tests by altering buffer lengths

To relieve the potential concern of using the 3-miles buffer length, I conduct a sensitivity analysis to investigate the potential impact of altering buffer lengths on my estimations. I apply two forms of outcomes: (1) the household-level binary variable (heat pump adoption status); (2) the heat pump adoption density within a 500m*500m grid. When using the household-level outcome, I alter the buffer length from 1 mile to 5 miles (with 0.1-mile intervals) continuously and re-run the models for each buffer length. When using the grid-level outcome, I alter the buffer length from 2 miles to 5 miles (with 0.1-mile intervals) continuously. For sample 1, I apply the LPM-DID and DID models to estimate the rebate's effect. For samples 2 and 3, I estimate the difference in differential trends to compare the effect of the rebate with that of the loans.

Figure 2.6 plots the estimations along with the changing buffer lengths¹⁷. The changing impacts along with the changing buffer lengths are due to those different residents included in my samples. The impact of a policy on different groups or types of people can vary. For instance, some residents may not prefer heat pumps, such as houses without robust electrical wiring or residents who do not use space heating very often. The rebate effect on these types of homes can be much lower. Thus, after I change the buffer lengths, different residents are included, and different effect sizes are estimated. Nevertheless, my results show that all the estimations, regardless of the buffer length choice, are significantly positive at a 10% level, implying that changing buffer lengths have little impact on my estimations' statistical significance and the direction of impacts.

¹⁷ I do not make the scales in all three sub-graphs the same, since the effect size in the second subplot is much smaller than the other two subplots and it would be too small to be easily noted.

Among the buffer lengths, my estimations consistently show that the rebate can increase the household's probability of installing a heat pump and the effect of the rebate is larger than those of the other two loan programs. Thus, changing the buffer length will not change the main conclusion of this study.

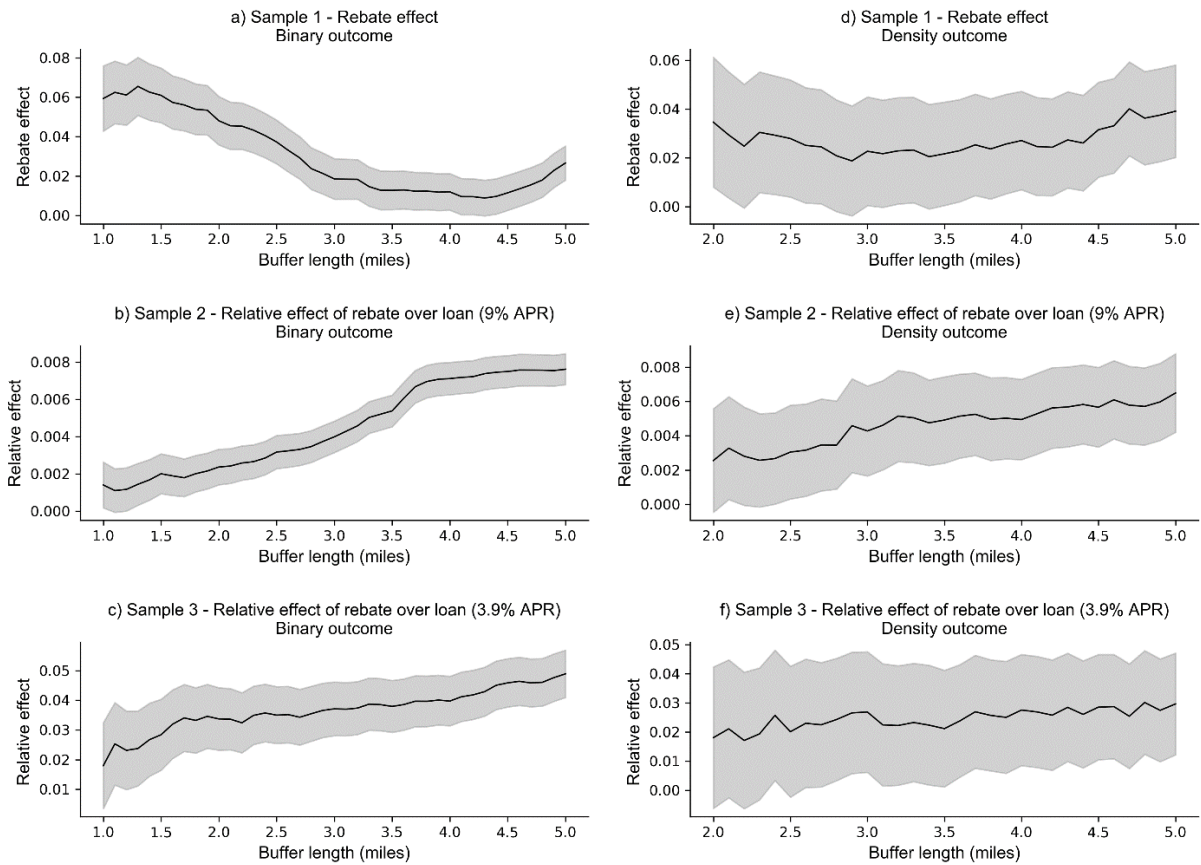


Figure 2.6 Robust checks by altering the buffer lengths

Note: black lines are point estimates and shaded areas are 95% confidence intervals

7. Heterogeneous rebate effects by income

The heat pump adoption rate is significantly positively correlated with personal income based on the analysis in section 2. Low-income households are less likely to adopt energy efficiency technologies (Zhao et al., 2012). High-income groups are more likely to afford extra upfront costs caused by heat pumps, while low-income groups are less likely to afford the extra upfront costs. A large body of literature has discussed this social-economic disparity of energy efficiency between low- and high-income groups (O’Shaughnessy et al., 2020; Sunter et al., 2019; Reames, 2020; He et al., 2020; Lou et al., 2020; Zhao et al., 2012). More incentives and supports are needed for low-income groups to improve their building energy efficiency and reduce their energy bills. An important policy question is whether the current form of incentive (e.g., cash rebate, low-cost financing) can increase energy efficiency investments for low-income groups. In this section, I investigate the heterogeneous effects of the rebate program on heat pump adoption rates across different income levels.

To estimate the heterogeneous rebate effects, I use the same research design as the first study (using the DID model and sample 1) and add interaction terms between the treatment variable and a series of indicators of income intervals. Here, I divide the household income¹⁸ into six intervals, including “<20K”, “20K-30K”, “30K-40K”, “40K-50K”, “50K-60K”, and “>60K”. The econometric model is specified as follows:

$$Y_{it} = \gamma + \sum_{j=1}^j \beta_j D_{it} \cdot \text{Income Interval}_j + \varphi_i + \vartheta_t + \varepsilon_{it} \quad \dots (13)$$

¹⁸ To create the variable of income at the grid level (500m*500m), I applied two steps: First, based on households’ longitude and latitude, I match each household with a corresponding census block group-level income. Second, I compute the average income within a grid by averaging the households’ incomes (obtained from the first step).

where Y_{it} is the residential heat-pump installation rate within a 500m×500m grid i in time t . D_{it} is the treatment variable, which takes value one for grids in the Duke Energy utility after the implementation of the rebate program and takes value zero otherwise. φ_i is individual grid fixed effects. ϑ_t is year fixed effects. ε_{it} is the error term. **Figure 2.7** plots the estimates.

The effect of the rebate program on heat pump adoption rate increases with income until income reaches about 60K. There are several reasons to explain this finding. Low-income households may suffer from credit and liquidity constraints and cannot afford the upfront costs of heat pumps even with the rebate. The cost burden of building retrofits can be much higher for low-income households given their limited disposable income, while the future benefits of building energy efficiency retrofits can be smaller for low-income households since their energy consumption is much less than higher-income groups (Yanagisawa and Data, 2012; Jamasb and Meier, 2010). In addition, low-income groups are more likely to be risk averse (Shaw, 1996) and hesitant to install new technologies such as heat pumps.

Also, I find that the rebate program is not effective for households with the highest income interval. This could be due to that higher-income households may care more about other visible competing technologies (such as solar panels, electric vehicles, and home battery storage) than the heat pumps.

The penetration rate of heat pumps in low-income communities is lower than in rich communities, and the current rebate incentive is also relatively less effective for low-income communities. From an equity perspective, government agencies and utilities should explore other effective and innovative policies to support low-income communities. This study only investigates the heterogeneous effects of the rebate program but not the low-interest loan program since I can

only conduct a robust DID estimation for the rebate program. Future research could explore the effects of other policies (including the low-interest loan) on low-income communities.

See **Appendix K** for alternative heterogeneous rebate effects by income quartiles.

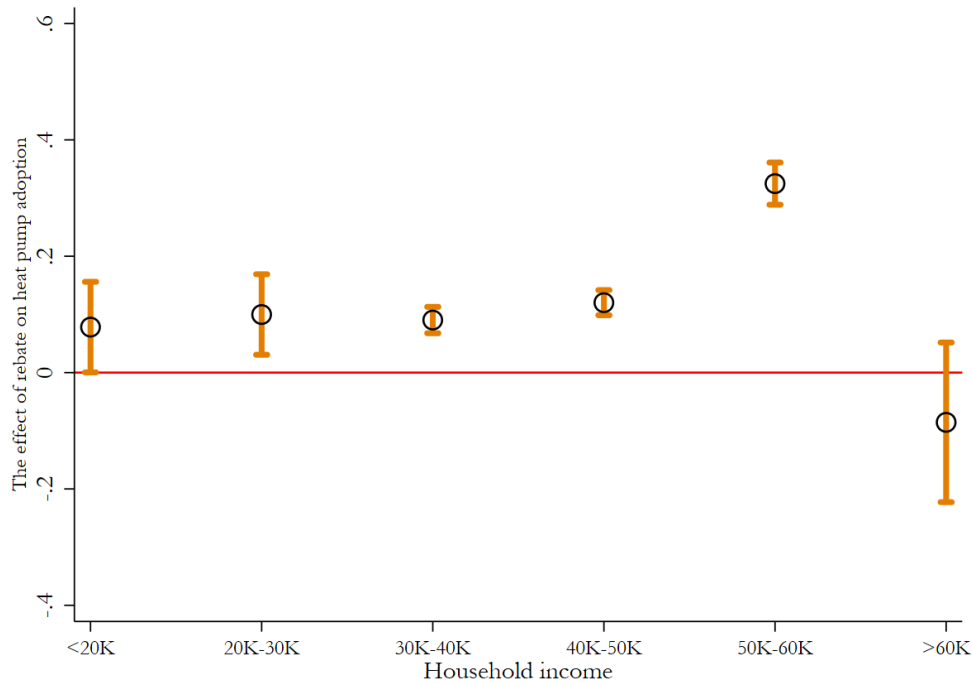


Figure 2.7 The heterogeneous effects of the rebate program on heat pump adoption rate (share of households with heat pumps within a 500m*500m grid) by income using DID approach.

Note: In the figure, circles are point estimates, and error bars are 95% confidence intervals.

8. Cost-effectiveness analysis

In this section, I compare the rebate program with loan programs in terms of cost-effectiveness. I use the amount of dollars spent per heat pump adopted caused by the incentive to measure the

cost-effectiveness. The cost-effectiveness (σ) of the incentive program is computed by the following equation:

$$\sigma = \frac{k \cdot (n + \Delta) \cdot c}{\Delta} = c + \frac{kn}{\Delta} c \quad \dots (14)$$

where Δ is the heat pump adoption growth induced by the policy; n is the heat pump natural adoption growth without the incentives (if the incentives had not been in place); k is the proportion of residents who apply for the incentive in residents with new heat pump installations; c is the program cost paid for each application (including the natural adoption of the heat pump). For the rebate program, c_R equals the rebate amount, which is \$300 to \$450. For the loan program, c equals the difference in the loan principal and the present value of repayments, and is computed according to the following equation:

$$c_L = P - \sum_{i=1}^5 \frac{P \cdot (r_{APR}/12)}{1 - (1 + r_{APR}/12)^{-n}} \cdot \frac{12}{(1 + r_{S\&P})^i} \quad \dots (15)$$

where c_L is the loan program cost for each application; P is the amount of loan principal; r_{APR} is the annual interest rate of the loan; $r_{S\&P}$ is the S&P 500 (a stock market index) annualized return rate from 01.01.2015 to 01.01.2020 (a five-year period), which is 10.08%; n is the number of monthly repayments. Here, I consider a common amortization loan program, which spreads out a loan into a series of monthly fixed payments. The two loan programs in my study are both five-year loan programs. I assume every loan applicant applies for an \$8,000 five-year loan program for the heat pump, and then calculate the sum of the present value of each year's repayment using

the S&P 500 annualized return rate as the discount rate. The discount rate should reflect the return of alternative investments for loan lenders. Using the above equation, c_L equals \$461 for the loan program with 9% APR, and c_L equals \$1,328 for the loan program with a 3.9% APR. Thus, I find that $c_R < c_L$. Based on my previous estimations, the rebate's effect is larger than the other two loan programs, so $\Delta_R > \Delta_L$. If I assume that the application proportions of the rebate program and the loan program are the same ($k_R = k_L$), I have:

$$c_R + \frac{n}{\Delta_R} \cdot c_R < c_L + \frac{n}{\Delta_L} \cdot c_L \quad \mathbf{s.t.} \quad c_R < c_L, \Delta_R > \Delta_L \quad \dots (16)$$

$$\sigma_R < \sigma_L \quad \mathbf{s.t.} \quad c_R < c_L, \Delta_R > \Delta_L \quad \dots (17)$$

As a result, the rebate program is more cost-effective than the loan program if the same proportions of residents applied for the rebate and loan programs. In other words, the amount of dollars spent per heat pump adopted induced by the rebate program is less than that by the loan programs. Note that I only consider monetary loss and do not take into the costs of program administration for both utilities and consumers. The administration costs of the loan program could be much higher than the rebate program because loans require more administration work such as credit history checks, application paperwork, and a series of repayments. Also, the funding-raising costs of the loan program are higher than the rebate program. For example, utilities need to give \$8,000 to each applicant in a loan program, while they only need to give \$450 to each applicant in a rebate program. If I consider these extra costs, the loan program should be much less cost-effective compared to the rebate program.

Policymakers should take several important factors into account when investigating the cost-effectiveness of incentives: the natural adoption growth without the intervention of incentives, the percentage of consumers who will apply for the incentives, and the causal effect of the incentives on the technology adoption. If the natural adoption growth without the intervention of incentives is high and those residents also apply for the rebate and loan programs, it would lead to the free-riding problem. With a high amount of freeriding, policymakers and utilities are better off not having incentives since this will lead to a high cost of the rebate and loan programs. Incentives (rebate and loan) targeted at specific marginal consumers whose willingness to pay is at the bottom edge of upfront costs could be applied to improve the cost-effectiveness of the incentives.

The rebound effects after installing heat pumps (Winther & Wilhite, 2015) may reduce the expected effect of incentives for heat pumps on decarbonization. Households can get energy bill savings from installing the energy efficiency technology and use these savings to increase energy consumption in other areas or within the same area for increased comfort. A study finds a rebound effect of 20% for consumers after replacing direct electric heating with air source heat pumps in Denmark (Gram-Hanssen et al., 2012). In the US, the rebound effect after heat pump adoption may also exist and reduce the expected effects of incentives, since increased electricity consumption produces air and carbon pollution. However, the rebound effect will not diminish the effect of heat pumps on decarbonization with a carbon-free power grid in the future.

Since I only estimate the rebate's effect based on sample 1 and I do not know the absolute value of the rebate and loans' effects in samples 2 and 3, I can only compute the absolute value of cost-effectiveness for the rebate program in sample 1. The computed cost-effectiveness of the rebate program in sample 1 based on a one-year time window is \$2,914-\$3,921 per heat pump if I assume every resident who installed the heat pump applied for the rebate. The cost-effectiveness

is much larger than the rebate amount (\$300-\$450) because the natural adoption growth in that region is quite high.

I also compare the cost-effectiveness of the rebate with the cost of carbon in **Appendix L**.

9. Discussion and implications

To tackle the crisis of climate change, decarbonizing the demand side through energy efficiency and electrification has been one of the most important strategies. Space heating accounts for almost two thirds of U.S. home energy consumption (EIA, 2018). Installing electric heat pumps provides an energy-efficient way to replace traditional natural gas furnaces or boilers for space heating. Many policies have been introduced to accelerate the transition to heat pumps. The cash rebate and low-cost loan have been the two most-widely adopted incentives to spur the building retrofit and improve energy efficiency. This study provides the first empirical evidence of the effects of rebate and loan incentives on residential air-source heat pump adoption rate based on three samples in North Carolina. I investigate three incentives, including a rebate (\$300-\$450) program, a loan program with 9% APR, and a loan program with 3.9% APR. I show that a rebate program (\$300-\$450) can increase the adoption rate by 0.024 in a year, around a 13% increase. I also conduct a rigorous comparative analysis of the incentive effects between the rebate and loan programs. I find that the rebate program shows advantages in promoting the growth of residential heat pumps for average consumers compared to the loan programs with 3.9% and 9% APR. When I investigate the cost-effectiveness of these incentives, I find that the rebate program is more cost-effective than the other two loan programs if the proportions of residents who apply for the rebate and the loan in residents with new heat pump installations are the same.

There are three potential concerns in my identification strategies due to the data limitation and the empirical context. First, in the last two samples, I utilize the difference in differential trends to compare the two loan and rebate incentives since a standard DID specification cannot be applied due to data restrictions. Interpreting the results from the last two samples should proceed with caution. I am unable to provide empirical evidence for the assumption of comparable demand for replacing old heating equipment across the two sides of the borderline. Nevertheless, my study provides a framework for future studies to compare the differential impacts between the rebate and loan programs on new green technology adoption. Second, the incentive policies may be endogenously determined by energy utilities as the company may choose a particular program based on what they thought would work best for their customers. This concern is relieved by the narrow buffer zone in my samples because residents share similar demographic and economic characteristics across the borderlines in my samples based on my balance test. Future field experiment studies may randomly assign the incentives to subjects to fully address the endogeneity issue. Third, since I did not observe the exact rebate amount received by consumers in my sample, I am unable to distinguish the impact of different rebate amounts on the heat pump adoption rate. The amount of rebate ranges from \$300-\$450 in my context, depending on the heat pump configuration and whether a smart thermostat was installed. While my primary interest is not comparing the impact of different rebate amounts, future research with individualized rebate amount data can explore the rebate elasticity of demand to find if consumers are sensitive to the rebate changes and what an “optimal” rebate level should be. Despite the potential concerns, my study contributes to the literature on the policy effects on energy technology adoption. Heat pumps have been the focus of energy scholars for at least ten years (Sopha et al., 2010; Hannon, 2015;

Snape et al., 2015), but no studies provide empirical evidence on the effect of the incentives targeted at heat pumps.

Interpreting the broader applicability of my results should be cautious. My study is focused on heat pump adoption, but utilities often have incentive programs for a wide array of energy-efficient products. The incentives not aimed at heat pumps may actively influence households' decisions on adopting heat pumps. That is, the parameter estimates from this study are conditional on all other policies in effect in my samples. If those contemporaneous energy efficiency incentives changed over time within the time window of my study, they may also impact my parameter estimates. By checking the Database of State Incentives for Renewables & Efficiency (DSIRE), I find that only one solar rebate program changed over time in my sample. Based on my analyses, the effect of solar rebate program could have only a very small effect on heat pump adoption (see **Appendix M**) and will unlikely change my main results. Also, my estimates are conditional on the site selections and sample characteristics, such as regional household income, the share of rental units, local residents' environmental friendly awareness, and others.

This paper focuses on heat pumps but also has implications for policies stimulating the adoption of other energy technologies, such as energy-star-qualified home appliances, solar water heating, and solar panel. My finding is consistent with Crago and Chernyakhovskiy (2017) about the incentive effect on residential solar photovoltaic (PV) adoption, where the rebates are most effective among financial incentives (including income tax credit, rebate, sales tax exemption, and third-party ownership), and an additional one dollar per watt rebate can increase the annual PV capacity additions by 50%. My estimated effect size of the rebate for air source heat pumps is smaller than that for residential PV solar panels in Crago and Chernyakhovskiy (2017)'s study. Wee et al. (2018)'s study used a national sample of 50 US states and found that a \$1000 increase

in the value of EV policies can increase new EV registrations by 5-11%. My estimated effect size of the rebate for air source heat pumps is larger than the policy effect on new EV adoption. Future research is needed to compare the impacts of cash rebates and low-cost loans on other technologies.

My study provides several implications for policymakers. First, this evidence-based study suggests that the rebate incentive effectively promotes the growth of heat pumps. Notably, many decarbonization plans have relied more on financial policy tools (e.g., rebate, low-cost loan) and planned to provide more funding for these policies, such as Joe Biden's prioritized climate policies and Massachusetts' three-year energy efficiency plan. My study shows circumstances where the rebate policy can be effective.

Second, the rebate program is more effective in promoting the growth of heat pumps than the low-interest loans based on North Carolina's evidence. This could be due to the well-developed credit market in the U.S. The average price of air-source heat pumps is about \$8,000. Most residents can obtain this amount of personal loan from commercial banks or credit companies easily. Thus, the credit constraints for heat pumps are not binding for most consumers, and the major incentive effect of the utility's loan program is the lower interest rate. Without the problem of credit constraints, the low-interest loan and the cash rebate are two forms of subsidies. Consumers' inattention to the subsidies of low-interest loans and consumers' lower perceived discount rate toward future cash flows may lead to the better effectiveness of the rebate program (e.g., Sexton, 2015). In practice, policymakers also need to consider other factors to decide which policy to apply, such as cost-effectiveness, funding raising costs, program administration costs, and the share of people applying for the incentives. My calculation finds that the rebate program is the most cost-effective among the three incentives. If I count the higher costs of funding raising

and program administration of the loan program, the rebate program could be more cost-effective further.

Third, the rebate program is less effective for low-income groups than high-income groups. Low-income groups may not be able to afford the high upfront costs of energy efficiency investments. There may still be a gap between low-income people's willingness to pay and the adoption cost with the cash rebate. Thus, the current rebate policy is not effective for low-income groups. Policymakers could increase the amount of rebates for low-income groups to increase the influence of rebates. The penetration rate of energy efficiency technologies is lower in low-income communities, requiring more support from the government in the transition. To promote the adoption of heat pumps for all consumers, policymakers can introduce multiple types of policy tools at the same time, such as rebates, low-cost loans, energy efficiency audits, and many others. The loan program could relieve the credit constraints of low-income consumers. Future studies also need to evaluate the effects of the combination of different incentives.

Last but not least, my study also provides implications for other countries with the urgent need for space heating electrification. For example, China has set up an ambitious goal of "carbon neutrality" and introduced many incentives to encourage the adoption of heat pumps. In many rural areas of China, there is an urgent need to replace coal-fired furnaces with electric heat pumps but the majority of consumers there are low-income groups. My study suggests that multiple incentives in addition to the cash subsidies should be applied to further increase heat pump adoption in those low-income areas. More empirical studies are needed to provide robust evidence on the policy effects in other countries.

Appendix

Appendix A. The density of air-source heat pumps by the state in the U.S. in 2020.

State	HP density (Number/10K persons)	State	HP density (Number/10K persons)
North Carolina	903.25	South Dakota	22.23
Virginia	865.64	Iowa	21.41
Maryland	659.31	Massachusetts	15.81
South Carolina	572.16	Wyoming	15.28
Kentucky	332.33	DC	13.25
Washington	310.77	Arkansas	13.13
Oregon	244.66	Maine	11.41
Delaware	200.33	Minnesota	11.26
Tennessee	168.09	Connecticut	11.16
Nebraska	137.33	Mississippi	10.53
Kansas	127.99	Alabama	5.72
Georgia	108.06	New Hampshire	5.52
Pennsylvania	100.43	Rhode Island	4.02
Idaho	98.43	Michigan	3.63
Indiana	90.60	West Virginia	2.28
Oklahoma	81.68	Texas	2.00
Ohio	67.60	Colorado	1.95
Florida	60.05	North Dakota	1.24
Arizona	54.53	California	1.13
Montana	44.50	Alaska	0.98
Utah	42.02	New Mexico	0.93
Nevada	39.47	Wisconsin	0.24
Missouri	28.55		

Data source: ZTRAX database.

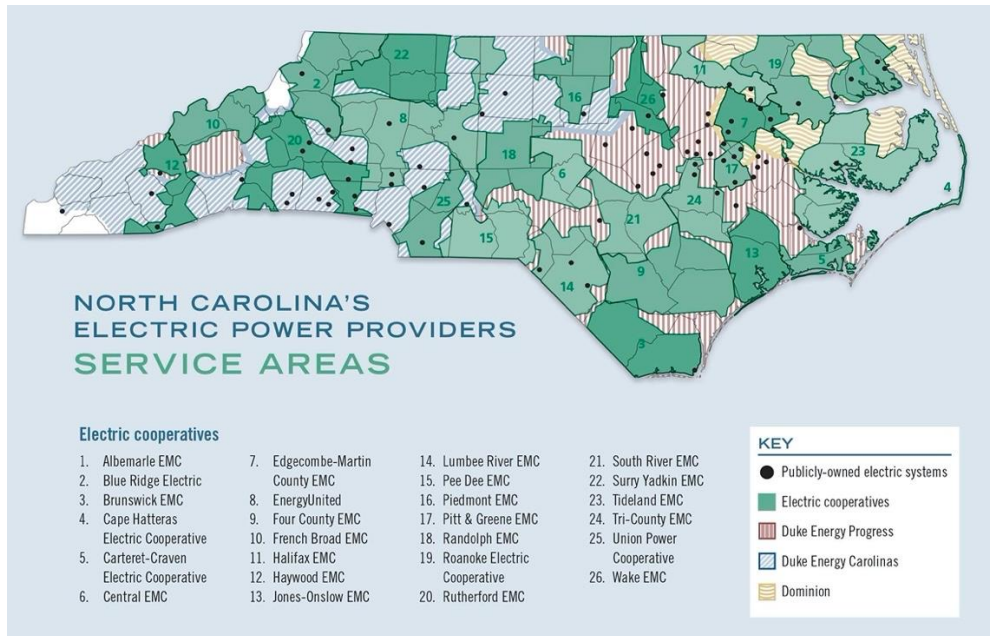
Appendix B. The correlation between heat pump adoption and other factors using the national county-level data

Supplementary Table 1. The correlation between heat pump adoption rate and other factors using national county-level data and an OLS model

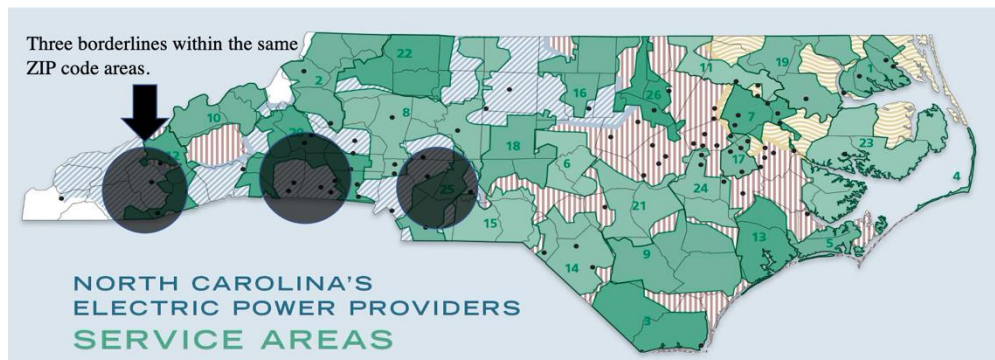
	(1)	(2)	(3)	(4)
	3142 counties		Excluding counties without heat pumps	
	<i>Original independent variables</i>	<i>Standardized independent variables</i>	<i>Original independent variables</i>	<i>Standardized independent variables</i>
Income per capita (2018\$)	0.0026*** (0.0008)	30.805*** (9.51)	0.0044*** (0.0017)	52.02*** (19.89)
Population density in 2018 (number/miles ²)	-0.005 (0.0047)	-8.966 (8.54)	-0.054** (0.026)	-97.97** (48.22)
Average residential electricity price in 2018 (cents)	-39.04*** (4.776)	-84.99*** (10.39)	-49.85*** (11.08)	-108.54*** (24.13)
Average residential natural gas price in 2018 (cents)	30.78*** (3.846)	95.01*** (11.87)	48.35*** (9.40)	149.28*** (29.01)
Environmental awareness level in 2015 (%)	1.47 (1.6390)	8.43 (9.38)	0.79 (3.57)	4.566 (20.49)
Average annual cooling degree days from 1981 to 2010	-0.199*** (0.017)	-212.5*** (18.56)	-0.248*** (0.039)	-265.23*** (42.02)
Average annual heating degree days from 1981 to 2010	-0.088*** (0.0097)	-178.1*** (19.6)	-0.174*** (0.022)	-350.758*** (44.98)
R2	0.0792	0.0792	0.1349	0.1349
Obs	2709	2709	1,236	1,236
Mean of outcome variable (number per 10,000 persons)	155	155	347	347

Note: *** p<0.01, ** p<0.05, * p<0.1. In column (2) and (4), I standardize the independent variables into variables with 0 mean and 1 standard deviation. I use the percentage of people who believe global warming is happening in a county to represent the level of environmental awareness (Yale Program on Climate Change Communication, 2019). Data sources: Bureau of Economic Analysis, U.S. Department of Commerce; U.S. Energy Information Administration; Yale Program on Climate Change Communication (Howe et al., 2015); ZTRAX dataset; National Oceanic and Atmospheric Administration.

Appendix C. The distribution of electric utilities in North Carolina



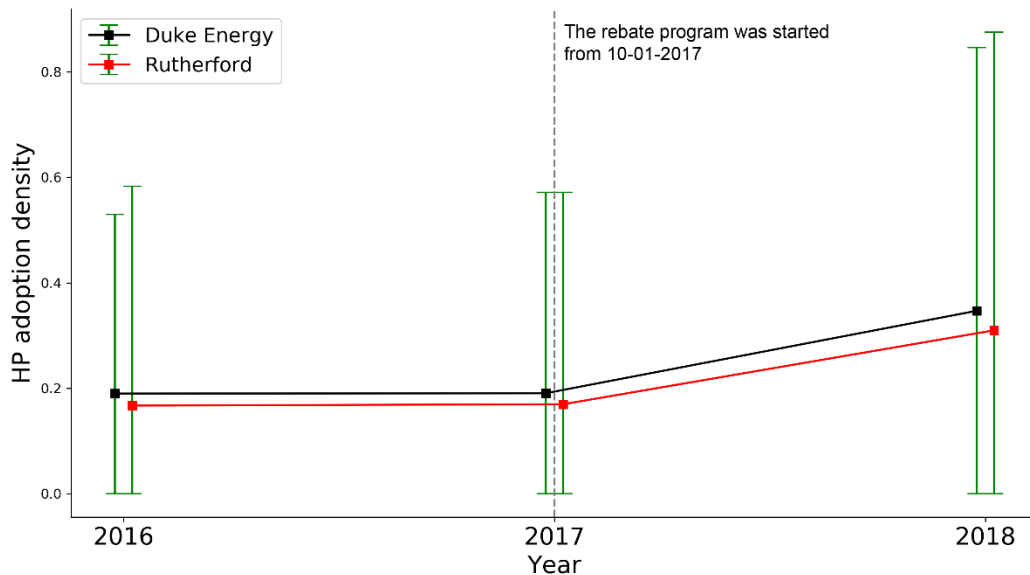
Supplementary Figure 1. The distribution of electric utilities in North Carolina. Figure source: Carolina country, https://www.carolinacountry.com/media/zoo/images/serviceareas_df2b99d1ada9ee3658733481c4b1f227.jpg



Supplementary Figure 2. The distribution of three borderlines (Duke Energy – Rutherford; Duke Energy – Union Power; Duke Energy – Brunswick) in the three studies. Figure source: Carolina country, https://www.carolinacountry.com/media/zoo/images/serviceareas_df2b99d1ada9ee3658733481c4b1f227.jpg

Appendix D. The heat pump adoption density before and after the rebate in sample 1

Supplementary Figure 3 shows the evolution of heat pump adoption density (within 500m*500m) across three years in the treatment and control groups in sample 1, respectively. For each year, I use all the observations within the year to calculate the average, the ten percentile, and the ninety percentile, which are plotted in the figure. **Supplementary Table 2** presents the detailed numbers of these descriptive statistics across these three years. In the treatment group and in 2016 before the introduction of the rebate policy, the average adoption density is 0.19. After the rebate policy, the average adoption density in the treatment group increased to 0.35. Also, I can find that the adoption density of heat pumps increased in both treatment and control groups. Thus, I utilized the DID method to compare the changes of adoption density before and after the rebate policy in the Duke Energy utility area (treatment group) with those in the Rutherford utility area (control group).



Supplementary Figure 3: The evolution of heat pump adoption density in the Duke Energy utility area (treatment group) and in the Rutherford utility area (control group) in sample 1. **Note:** The adoption density is computed within a 500 meters*500 meters' grid. The green bars show the ten percentile and the ninety percentile of the adoption densities.

Supplementary Table 2: The descriptive statistics of heat pump adoption density across years in sample 1

Year	Utility	Mean of adoption density	10 Percentiles	90 Percentiles	Standard Deviation
2016	Rutherford	0.1673	0.0000	0.5833	0.2821
2017	Rutherford	0.1698	0.0000	0.5714	0.2823
2018	Rutherford	0.3099	0.0000	0.8750	0.3315
2016	Duke Energy	0.1901	0.0000	0.5294	0.2744
2017	Duke Energy	0.1907	0.0000	0.5714	0.2767
2018	Duke Energy	0.3469	0.0000	0.8462	0.3189

Note: The adoption density is computed within a 500 meters*500 meters' grid.

Appendix E. Estimates of the rebate effect using Cox proportional hazards model

In my setting, the installation of a heat pump for an individual household can be regarded as a hazardous event. I focus on a period from 2017-11-02 to 2018-12-30 right after the introduction of Duke Energy's rebate program. I drop the houses that have installed the heat pump on 2017-11-02 from my sample and those remaining houses did not install the heat pump at the beginning of my study period. Since I can only observe house features from 4 periods (including 2017-11-02, 2018-01-07, 2018-08-05, 2018-12-30), I am not able to know the exact adoption dates of heat pumps. Thus, I suppose that if a house did not have a heat pump in one period and it had a heat pump in the following period, the house installed the heat pump in this following period. The survival time in the Cox model is supposed to be from 2017-11-02 to the date of heat pump adoption. In addition, I consider a censored proportional hazards model. Those houses that had not installed the heat pump at the end of my study period are regarded as "alive" or "censored" on 12-30-2018. Then, I fit the following model:

$$h(t)_{ic} = h_0(t)_{ic} \times \exp(\alpha D_i + \varphi_c)$$

where t represents the survival time; $h(t)_{ic}$ is the hazard function for household i in census block group c , meaning the hazardous risk at time t , or the probability of a hazardous event at time t ; $h_0(t)_{ic}$ is the baseline hazard function when all the covariates equal to zero; D_{ic} is the treatment group dummy, which takes value one for households in the Duke Energy utility area and takes value zero otherwise; φ_c is the census block group fixed effects, which can control for the time-fixed census demographic features at the block group level.

Estimation results are presented in **Supplementary Table 3**. I apply two different specifications by not adding or adding the census block group fixed effects. In both columns, the coefficients of the treatment dummy are positive significantly, suggesting that the rebate program

is positively associated with the event probability (the probability of adopting a heat pump). In other words, the rebate program can significantly increase the adoption of heat pumps, which is consistent with my baseline estimations.

Supplementary Table 3: Estimates of the rebate effect using Cox proportional hazards model

VARIABLES	(1) Model 1	(2) Model 2
$1[\text{Duke Energy}]_i$	0.055*** (0.02)	0.094*** (0.035)
Census block group fixed effects	No	Yes
Observations	27,346	27,346

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix F. Tobit estimates of the rebate effect

Using my first sample across two periods (2016-3-22 & 2018-08-05), I apply a Tobit model to estimate the effect of the rebate program. In the Tobit model, I regress the first differences of heat pump adoption density on a dummy variable indicating the Duke Energy utility area. Estimation results are shown in **Supplementary Table 4**. In column (2), I added the ZIP code fixed effects while I do not include them in column (1). The coefficients are significant and positive in both specifications. Based on column (2), results show the rebate program can increase the heat pump adoption density by 0.027 significantly in a one-year period, which is consistent with my baseline estimates.

Supplementary Table 4. Tobit estimates of the rebate effect		
	(1)	(2)
Outcome	Model 1	Model 2
	<i>First differences of heat pump adoption density within a 500m*500m grid</i>	
$1[Duke\ Energy]_i$	0.024** (0.011)	0.027*** (0.009)
ZIP code fixed effects	No	Yes
Pseudo R2	0.002	1.16
Observations	3,247	3,247

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix G. Robustness check of traditional RD in sample 1

For the RD-DID analysis in sample 1, a potential robustness check could be to consider just adoption outcomes in period 2 (08-05-2018) and then control for household characteristics in period 2. This would allow us to avoid any housing characteristic changes over time that may affect the result in the RD-DID. In this robustness check, I utilize a nonparametric local polynomial estimator, and a local linear regression with a triangular kernel function is applied. Since some variables of building characteristics have too many missing values (See the following **Supplementary Table 5**), I only controlled two building characteristics (building year built and the number of stories). I use the MSE-optimal approach (Imbens and Kalyanaraman, 2012) to compute the bandwidth employed for the RD point estimator, and a 0.788-miles bandwidth is chosen, leading to an effective sample size of 5,989 households. I use the robust bias-corrected (RBC) methods (Calonico et al., 2014, 2020) to compute the bandwidth for confidence interval interference and a 1.589-miles bandwidth is chosen. The result shows that the estimated coefficient of β is 0.00476, with a standard error of 0.03134 and a p-value of 0.879. The estimated effect is close to zero and insignificant, which could be due to two factors. First, I am not able to control for a sufficient number of variables of building characteristics in the RD model since there are so many missing observations of building characteristics. Second, the RD estimator in period 2 could be biased from the true rebate effect, since there might be other factors jumping at the cutoff along with the treatment (the rebate incentive). For instance, the two utilities may have different energy efficiency incentives. My baseline RD-DID approach has the advantage of ruling out all the time-invariant confounding factors (including the time-invariant energy efficiency incentives). As for the time-variant confounders, although the building characteristics may change over time, the time trends of changing building features should be consistent between the treated and control houses

at the cutoff borderline, since the probability of being treated at the cutoff is the same for each house at the cutoff. Thus, I think the RD-DID approach better reflects the treatment effect.

Supplementary Table 5. Descriptive Statistics of Building Characteristics in Sample 1

Variables	Obs.	Mean	Std. Dev.	Total Sample Size
Year built	33,097	1969.969	26.148	44,810
No. of stories	31,467	1.088	0.255	44,810
No. of rooms	735	5.975	1.576	44,810
No. of bedrooms	9,296	2.908	0.817	44,810
No. of bathrooms	9,341	1.795	0.793	44,810
Building condition	9,102	4.242	0.875	44,810

Appendix H. Ruling out the potential influences of unbalanced covariates in sample 3

Although the third sample is overall balanced, there are two imbalanced observable covariates, namely population median age and building's year remodeled. To fully rule out the potential influences of the two imbalanced covariates, I conduct a robustness test by directly controlling the covariates in my differential-trends model. I use the first differences of the heat pump adoption statuses at the individual household level as the outcome variable. A regression model is applied as follows:

$$\Delta Y_{i,t_1,t_2} = \beta D_i + X_i + \varepsilon_i$$

where $\Delta Y_{i,t_1,t_2}$ is the first difference of a binary variable indicating whether household i installs a heat pump in time t . D_i is a binary treatment group variable, which equals one if household i is located in the Duke Energy utility. X_i is the time-invariant observable unbalanced covariant. ε_{it} is the error term. Estimated results are shown in **Supplementary Table 6**. The estimations are insensitive to adding the control variables (population median age and building's year remodeled).

Supplementary Table 6. Robustness tests by adding unbalanced covariates

Model	(1)	(2)	(3)
β	0.04*** (0.005)	0.06*** (0.014)	0.04*** (0.005)
Control Variables:			
Building year remodeled	No	Yes	No
Population median age	No	No	Yes
R square	0.003	0.011	0.004
Obs	23,517	2,327	23,517

Note: *** p<0.01, ** p<0.05, * p<0.1.

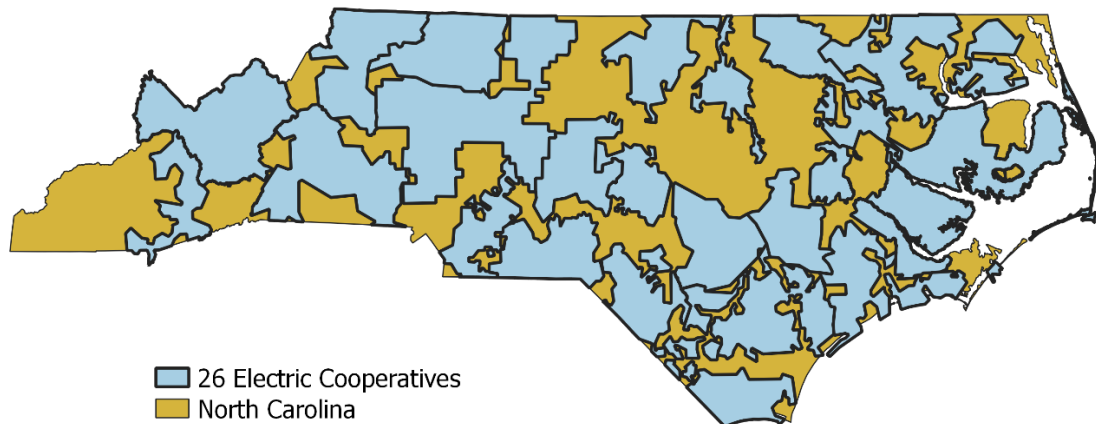
Appendix I. The impact of electricity price on heat pump adoption rate in North Carolina

I estimate the impact of electricity prices on heat pump adoption rate based on about 1 million residential buildings across 26 Electric Membership Cooperatives of North Carolina. **Supplementary Figure 4** plots the distribution of these EMCs. I apply the following two-way fixed effect model using yearly panel data from 2016 to 2019:

$$Y_{iut} = \beta P_{ut} + \varphi_i + \vartheta_t + \varepsilon_{iut}$$

where Y_{it} is the heat pump adoption rate within a 1km×1km grid i and on year t . I calculate the yearly heat pump adoption rate based on four assessments of ZTRAX database which were conducted on 02/03/2017, 01/07/2018, 12/30/2018, 01/02/2020, respectively. P_{ut} is the average electricity residential price (cents) of utility u on year t . Different utilities have different electricity prices. I calculate the yearly average residential electricity price by dividing the cooperative's residential total revenue by residential sales based on EIA 861 forms from 2016 to 2019. The EIA 861 forms were obtained from the website of Annual Electric Power Industry Report, U.S. Energy Information Administration. φ_i is the individual grid fixed effects. The heterogeneous incentives for heat pumps provided by different cooperatives can be controlled by the individual grid fixed effects. ϑ_t is the year fixed effects controlling for common time trend of heat pump adoption rate. I cluster the standard error at the individual grid level.

Supplementary Table 7 presents the estimation result. The coefficient of the electricity price variable is negative and significant. One cent of decrease in residential electricity price can lead to the heat pump adoption rate increasing by 0.0016 in North Carolina.



Supplementary Figure 4. The distribution of Electric Membership Cooperatives in North Carolina

Supplementary Table 7. The impact of electricity price on heat pump adoption rate in North Carolina

Variables	Coef.	Std. Err.	P-value
Electricity price	-0.0016	0.0005	<0.01
1[year=2017]t	0.0036	0.0003	<0.01
1[year=2018]t	0.0151	0.0005	<0.01
1[year=2019]t	0.0161	0.0005	<0.01
Constant	0.1723	0.0067	<0.01

R-square: 0.003

Obs: 238,492

Note: Individual grid fixed effects and year fixed effects are included in the two-way fixed effects model. The standard errors are clustered at the individual grid level.

Appendix J. The amounts and percentage of personal loan and credit card debt in the U.S.

Supplementary Table 8. The amounts and percentage of personal loan and credit card debt in the U.S.

Panel A: Personal Loan				
Year	Average Personal Loan Balance	Percentage of Personal Loan Balance (\$20K or less)	Percentage of Personal Loan Balance (\$20K - \$40K)	Percentage of Personal Loan Balance (\$40K or more)
National:				
2019	\$16,181	79.70%	11.80%	8.50%
2018	\$16,263	80.10%	11.40%	8.50%
2017	\$16,421	80.40%	11.10%	8.50%
2016	\$16,443	80.70%	10.90%	8.40%
2015	\$15,646	82.20%	10.40%	7.40%
North Carolina:				
2019	\$16,359.89	78.70%	11.20%	10.00%

Panel B: Credit Card Debt in 2018

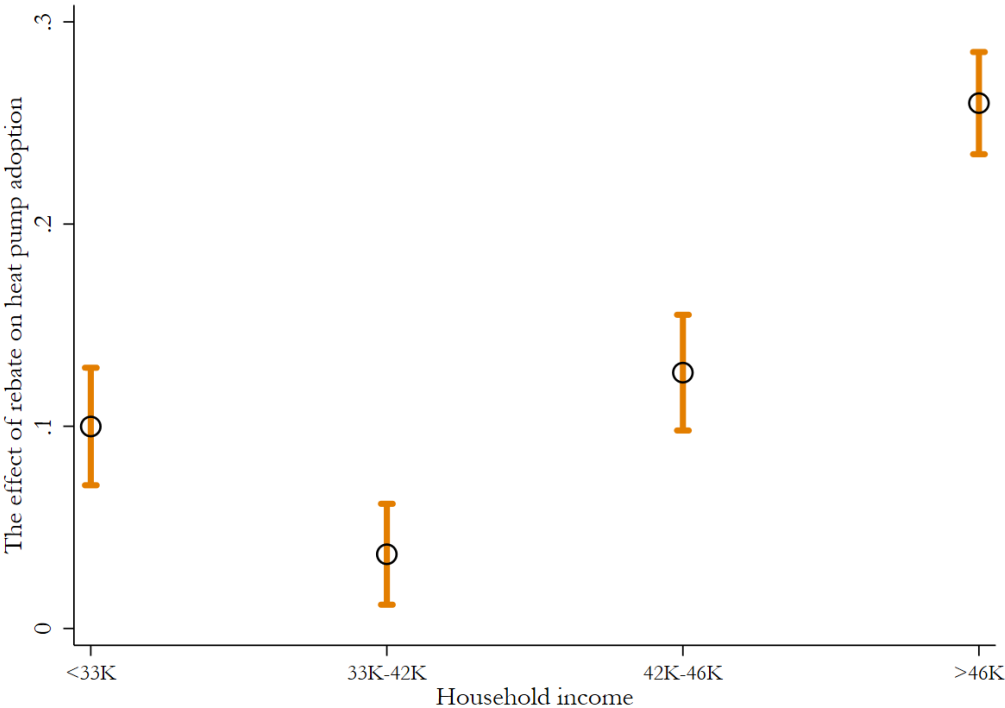
Average American Household Credit Card Debt: \$5,700.

Percentage of All American Households Carry Credit Card Debt: 41.2%

Average Household Credit Card Debt in North Carolina: \$7,225

Data sources: U.S. Census Bureau, U.S. Federal Reserve, 2019 Survey of Consumer Finances.

Appendix K. The heterogeneous effects of rebate on heat pump adoption by income quartiles



Supplementary Figure 5. The heterogeneous effects of the rebate program on heat pump adoption rate (share of households with heat pumps within a 500m*500m grid) by income quartiles using DID approach. (In the figure, circles are point estimates, and error bars are 95% confidence intervals.)

Appendix L. Comparing the cost of the policy with the cost of carbon

It is important to discuss the relationship between the cost of instruments (or the cost-effectiveness defined in section 8) and the cost of carbon. I find two challenges to conducting this analysis. First, it is difficult to calculate the absolute value of the cost-effectiveness of the rebate and loan programs. The cost-effectiveness (σ) is defined as the amount of dollars spent per heat pump adopted caused by the incentive and can be computed using the following equation:

$$\sigma = \frac{k \cdot (n + \Delta) \cdot c}{\Delta} = c + \frac{kn}{\Delta} c$$

where Δ is the heat pump adoption growth induced by the policy; n is the heat pump natural adoption growth without the incentives (if the incentives had not been in place); k is the proportion of residents who apply for the incentive in residents with new heat pump installations; c is the program cost paid for each application (including the natural adoption of the heat pump). In reality, I am not able to observe the k , and the n varies a lot across different sites or samples. Thus, it is difficult for us to compute the absolute value of cost-effectiveness. Also, results will depend on site selections because of the large variations in the cost-effectiveness across different sites.

Second, the avoided costs of carbon associated with the switches from typical natural gas furnaces to air source heat pumps can be time-variant since it depends on the carbon emissions from electricity generation. Although currently coal and natural gas power plants are still in service, more and more clean energy sources (e.g., wind and solar power) will replace the traditional fossil fuel sources in the near future, which generate zero carbon emissions. The avoided costs of carbon will be much larger in the future with more clean energy sources in the power grid. These clean energy sources are expanding very quickly these years. As a result, it is hard for us to predict the future carbon emissions of electricity generation in this paper and the avoided costs of carbon associated with switching to heat pumps in the near future.

To summarize, there are two major challenges to comparing the costs of policies with the avoided costs of carbon. To address these challenges, I make the following assumptions: 1) every resident who installed the heat pump applied for the rebate; 2) under the sustainable development scenario, the electricity generation produces zero carbon emissions. Based on the first assumption, I estimated the cost-effectiveness of the rebate program, which is \$2,914-\$3,921 per heat pump (see section 8). Based on the second assumption, the avoided costs of carbon are the social costs of carbon emissions from a typical natural gas furnace. According to Vaishnav & Fatimah (2020)'s study, the average annual CO₂ emission from one typical natural gas furnace in North Carolina (NC) is 4,266 lbs. I then use the following equation to calculate the present value of the lifetime social carbon costs of the natural gas furnace (Ω):

$$\Omega = \sum_{t=2020}^{t+n} e \cdot P_t$$

where e is the annual CO₂ emissions from a typical natural gas furnace in NC. P is the social cost or carbon price of CO₂ in year t , and I apply the values of social cost of CO₂ by years (from 2021 to 2025) provided by the US Environmental Protection Agency (2016). n is the number of years that the natural gas furnace can operate for and I suppose the natural gas furnace is installed in 2020 and it will be used for 25 years. After calculation, Ω equals 3400 (in 2021 dollars). So, I can find that the Ω is within the range of the cost-effectiveness of the rebate program in sample 1. In other words, the costs of the rebate program in sample 1 can be compensated by the avoided carbon costs associated with the switches from natural gas furnaces to heat pumps. The cost-effectiveness of rebate in sample 1 is much larger than the rebate amount (\$300-\$450) because the natural adoption growth in that region is quite high. In regions with lower natural adoption growth of heat pumps (or, fewer “free riders”), the costs of the policy can be much lower. A similar

calculation for the loan program is not possible since I cannot estimate the absolute value of the loans' effects in samples 2 and 3, due to data limitations.

Appendix M. Contemporaneous energy efficiency incentives programs

I check the incentives for energy efficiency products in my sample areas from the Database of State Incentives for Renewables & Efficiency (DSIRE). Based on the ZIP code, I can identify all the energy efficiency and renewables incentives in my sample areas. In my samples, I find 48 incentives in total since 2000. Among these 48 incentives, only one incentive program (in addition to the heat pump rebate and loan programs) changed over time within the period of my study (2016-03-22 to 2020-01-02), which is Duke Energy Solar Rebate Program (initiated from 09/24/2018). The effect of the solar rebate program could be one potential confounding factor in my study. To check the potential correlation between solar PV adoption and heat pump adoption, I utilized the 2015 Residential Energy Consumption Survey (RECS) database (EIA, 2020, <https://www.eia.gov/consumption/residential/data/2015/>), which is a U.S. nationwide representative sample of households. Using the RECS data, I conducted a Probit model by regressing the dummy of solar PV adoption on the dummy of heat pump adoption. The result shows that the marginally increased probability of installing a heat pump for a household with solar PV is only 1.3% (P-value <0.01), which indicates that the effect of solar PV adoption on heat pump adoption can be very small, and the effect of the solar rebate program on heat pump adoption will be much smaller or even negligible.

Chapter 3: Essay 2 - Estimation of Change in House Sales Prices in the US after Heat Pump Adoption

Abstract

Electrifying most fossil-fuel-burning applications provides a pathway to achieve cost-effective deep decarbonization of the economy. Heat pumps offer a feasible and energy-efficient way to electrify space heating. Here I show a positive house price premium associated with air-source heat pump installations across 23 states in the U.S. Residences with an air-source heat pump enjoy a 4.3-7.1% (or \$10,400 - \$17,000) price premium on average. Residents who are environmentally conscious, middle class, and live in regions with mild climate are more likely to pay a larger price premium. I find that estimated price premiums are larger than the calculated total social benefits of switching to heat pumps. Policymakers can provide information about the estimated price premium to influence the adoption of heat pumps.

1. Introduction

The increase in global average temperature must be kept below 1.5 degrees Celsius above the pre-industrial level to avoid irreversible environmental damage, which requires the carbon dioxide emissions to be reduced, or captured and sequestered (Masson-Delmotte et al., 2018). Electrifying most fossil-fuel-burning applications based on renewable sources provides a pathway to achieve cost-effective deep decarbonization of the economy (Denis et al., 2015; Hultman et al., 2019). While it is economical and technologically easier to sequester emissions from large sources such as electric power plants, reducing emissions from small distributed sources, including tens of

millions of natural gas furnaces used to heat homes and offices, is more difficult. Without the electrification of space heating, a large amount of carbon emissions are generated from burning natural gas in space heating even if I reach a cleaner electricity grid.

Studies typically identify the electrification of space heating by using air-source or ground-sourced heat pumps as a technologically straightforward way to replace fossil-fuel-burning furnaces or boilers (Davis et al., 2018; Lucon et al., 2014; MacKay, 2008; The heat is on, 2007). An increasing number of national, state, and municipal decarbonization plans have relied on the diffusion of heat pumps. For instance, the Dutch government plans to electrify buildings and fully phase out natural gas by 2050. The Irish government plans to install 600,000 highly efficient heat pumps by 2030. Finland sets a carbon neutral target by 2035, which includes a shift to electric heating by heat pumps. Massachusetts in the U.S. offers incentive programs for switching to heat pumps from furnaces. From a social planner's perspective, promoting heat pumps to electrify space heating will help reach deep decarbonization with a clean electricity grid. In addition, heat pumps offer an energy-efficient way for space cooling given a huge potential demand for air-conditioning in developing countries (Biardeau et al., 2019), help to balance electricity demand through demand-side smart management given the high penetration of renewable energy in the grid in the future, and relieve the problem of natural gas infrastructure constraints in the winter when there is a peak demand of natural gas for heating in the northern U.S.

Residential installations of air-source heat pumps have increased in recent years in the U.S. The distribution across states is not balanced. The Pacific, Mountain, South Atlantic, and West North Central regions enjoy a higher penetration of air-source heat pumps, while other regions have a much lower penetration, which implies a large potential for further growth (See **Figure 3.1** for the distribution of air-source heat pump penetration in the U.S. in 2018). The heterogeneous

growth of air-source heat pump installations begs the question of whether this new technology has been recognized in the housing market. My study investigates how the installation of air-source heat pumps affects house prices in the U.S., and whether the presence of a heat pump increases house values (i.e., a heat-pump-induced price premium). The heat-pump-induced price premium provides useful information for sellers and buyers to better assess house values as well as the technology value. More importantly, a positive price premium associated with the presence of air-source heat pumps can be useful for policymakers to design informational programs to influence the adoption and diffusion of heat pumps. For instance, the government can highlight the positive price premium induced by heat pumps and put a certified “energy-efficient heat pump” label on homes with heat pumps in an information campaign.

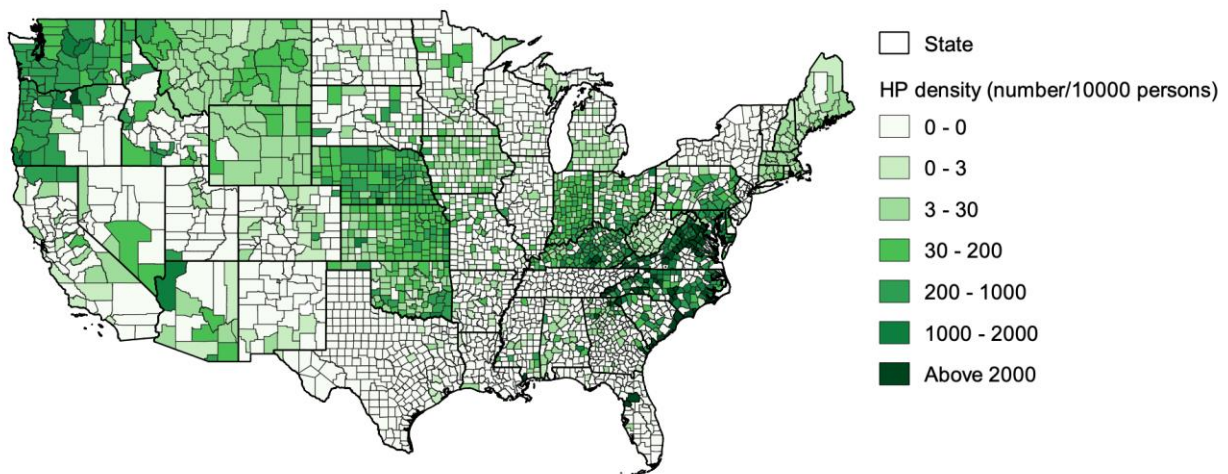


Figure 3.1 The density of air-source heat pumps (number/10000 people) by county level in the U.S. in 2018.

Several studies (Aydin et al., 2018; Qiu et al., 2017; Hoen et al., 2012; Dastrup et al., 2012) provide evidence on the price premiums of residential properties after installing solar panels or

solar water heaters, and the premiums range from 3.5%-17%. Other studies (Walls et al., 2017; Kahn and Kok, 2014; Deng et al., 2012; Deng and Wu, 2014; Brounen & Kok, 2011; Jayantha & Man, 2013) look at the capitalization of residential energy efficiency investment into property values and find that the property price premiums with energy efficiency rating or green-building labeling range from 2%-10%. Studies on commercial properties (Eichholtz et al., 2010, 2013; Costa et al., 2018) also find that green-certified office buildings enjoy a premium on transaction prices or rents. Existing studies of the price premium from energy efficiency mostly focus on green certification or energy efficiency ratings, not on specific technologies such as heat pumps. Despite the benefits from energy efficiency investments, there is a persistent gap between the level of energy efficiency investment that is projected to save money, and the investment that actually occurs (Fowlie et al., 2018). Common explanations focus on market failures, such as imperfect information, capital market failures, split incentive problems, and consumer behavior (Allcott & Greenstone, 2013; Gillingham & Palmer, 2014; Gerarden et al., 2015). Fowlie et al. (2018) and Liang et al. (2018) find that the actual energy savings are lower than engineering models' predictions.

This paper contributes to the literature using hedonic pricing methods to value energy technologies and energy efficiency investment. This study provides the empirical evidence of the house price premium induced by air-source heat pumps and its heterogeneity by different influencing factors. This paper also contributes to the literature on the “energy efficiency gap.” In my research, I find a large house sales price premium induced by air-source heat pumps, providing a strong incentive for installing heat pumps. The positive house sales price premium can be regarded as a significant private benefit in energy efficiency investment, which helps close the “energy efficiency gap”. This study produces three key findings. First, I provide the estimates of

house sales price premium induced by air-source heat pumps using observations across 23 states of the U.S. I find residences with an air-source heat pump enjoy a 4.3-7.1% (or \$10,400 - \$17,000) price premium on average. Second, I explore the heterogeneity of the price premium by investigating its relationship with other factors. Results show that residents who are environmentally conscious, middle class, and live in regions with mild climate are more likely to pay a larger price premium. Third, I compare the price premium with the benefit and cost of switching from a traditional HVAC system to an air-source heat pump. I find that the estimated price premiums are larger than the installation costs of heat pumps and larger than the calculated total social benefits of switching to heat pumps.

2. Data and methods

2.1 Data

In this study, I utilize the Zillow Transaction and Assessment Database (ZTRAX), which is obtained from Zillow. The 4TB of data covers more than 150 million homes in 51 states with building characteristics (heating types, rooms, area, view, land value, building quality, year built, etc.) for each house from six assessments conducted from 2016 to 2018, as well as historical transaction records since 1900 across the U.S. So, there are two parts of the dataset: assessment data and transaction data.

The assessment data include six property assessment datasets recorded on 3/22/2016, 2/03/2016, 7/31/2017, 11/02/2017, 1/07/2018, and 8/05/2018 (thus forming a panel dataset at the individual building level). The assessments were conducted repeatedly by Town/County tax assessor officers for property tax purposes. Any remodeling or upgrades above a certain level are

required by the local laws and regulations to be reported to the local tax assessor office so that the office can update the property characteristics. The Zillow company aggregates all the data from the local Town/County tax assessor offices and forms a national dataset. The assessment datasets provide information on property addresses, prior assessor valuations, and individual building characteristics (such as year built, year remodeled, building condition, building quality, number of stories, number of total rooms, number of bedrooms, number of bathrooms, building area, land assessed value, lot size, swimming pool, and site characteristics). The assessment data include approximately 200 million parcels in over 3,100 counties.

The transaction data include information from more than 374 million detailed public transaction records across over 2,750 counties for residential and commercial properties since the early 1900s. The sales price is the key outcome variable of this study, which is converted into current (2018) dollars adjusted by inflation rates. See **figure 3.2** for the illustration of the dataset structure.

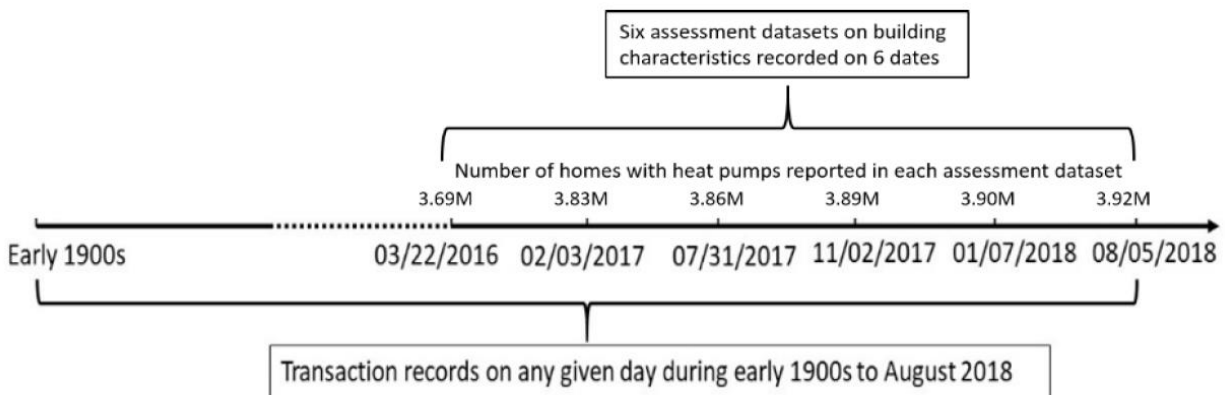


Figure 3.2 Summary of ZTRAX datasets and heat pump installation information

In the ZTRAX data, I can observe the heating and air conditioning types of each property in six time nodes. **Table 3.1** presents all the heating and cooling types shown in ZTRAX data. An

air-source heat pump is recorded as “HP” in the dataset, while a ground-sourced heat pump is recorded as “GT” in the dataset. In this study, I focus exclusively on the air-source heat pump. I can identify the heat pump installations by comparing the difference in heating types between two consecutive assessments. If the heating types differ in two consecutive assessments and in the later assessment the heating type is an air-source heat pump, a house installed the heat pump during the time window between the two assessments. Based on the heat pump installation dates, I categorize the transaction prices as pre- or post-treatment prices.

Table 3.1 Heating and air conditioning system type of houses in ZTRAX data

<i>Heating System Type</i>		<i>Air Conditioning Type</i>	
<i>Code</i>	Description	Code	Description
<i>BB</i>	Baseboard	CE	Central
<i>CE</i>	Central	CW	Chilled Water
<i>CL</i>	Coal	EC	Evaporative Cooler
<i>CV</i>	Convection	GT	Geo Thermal
<i>EL</i>	Electric	NO	None
<i>FA</i>	Forced air	OT	Other
<i>FL</i>	Floor/Wall	PA	Packaged AC Unit
<i>GS</i>	Gas	PR	Partial
<i>GT</i>	Geo Thermal	RF	Refrigeration
<i>GV</i>	Gravity	VN	Ventilation
<i>HP</i>	Heat Pump	WA	Wall Unit
<i>HW</i>	Hot Water	WU	Window Unit
<i>NO</i>	None	YY	Yes
<i>OL</i>	Oil		
<i>OT</i>	Other		
<i>PR</i>	Propane		
<i>PT</i>	Partial		
<i>RD</i>	Radiant		
<i>SM</i>	Steam		
<i>SO</i>	Solar		
<i>SS</i>	Space/Suspended		
<i>VT</i>	Vent		
<i>WB</i>	Wood Burning		
<i>YY</i>	Yes		
<i>ZN</i>	Zone		

The control group consists of the houses using one traditional heating system (Gas, Coal, Hot Water, None, Oil, Radiant, Steam, and Wood Burning) and air conditioning system (Center

Air-Conditioning, Packaged AC Unit, Evaporative Cooler, Ventilation, and None), and were sold at least twice during a similar data window. To make the sales dates of the control group close to those of the treatment group, I limit the second sales dates of the control group to be after 2016. All the transaction records in my analysis are from 2000 to 2018. I also remove the houses that were remodeled after the year 2000 from my sample to rule out the influence of remodeling on the estimation of the price premium. These houses remodeled after 2000 only account for a small portion (4%) of my full sample. Finally, I match treated houses and control houses in the same county to obtain 14,211 houses in the treatment group and 440,168 houses in the control group across 23 states for my baseline Difference-in-Differences analysis.

2.2 Empirical strategy

I apply the Difference-in-Differences (DID) method with exact matching at the county level to compute the treatment effect of the installation of air-source heat pumps on house prices based on the ZTRAX data across the U.S. I also apply several alternative econometric approaches as robustness checks.

There are three common challenges to estimating the average treatment effect on treated, including the selection bias, omitted variable bias, and model dependence. Many cross-sectional studies apply the outcome of units in the control group as the counterfactual, which potentially leads to selection bias (Angrist, 2008). In the context of the housing market, the price of a heat-pump house if it had not installed the heat-pump may be different from the price of a comparable house in the control group. The second major concern is that the assignment to the treatment group may be correlated with unobservable variables which also influence the outcome of interest

(Imbens, 2004). The treatment variable then becomes endogenous. For instance, the level of education in a region could be an unobservable variable, which influences residents' environmental protection awareness and further influences the installation of heat pumps. The level of education also affects personal income and house prices. Another major concern is model dependence. The actual relationship between variables may not be consistent with the assumed models. For instance, most studies applied a hedonic linear regression model to estimate house values. The conditional expectation function could be nonlinear and lead to biased estimation. To address these concerns, I utilize the method of Difference-in-Differences (two-way fixed-effect model) to estimate the treatment effect of adopting a heat pump on the house sales price. I also adopt other methods for robustness checks and heterogeneity analysis. Below I describe each method in detail.

2.2.1 Baseline method: Difference-in-Differences

To address the concern of selection bias and omitted variable bias, this study applies the Difference-in-Differences method to obtain the treatment effect based on the following equation (Lechner, 2010):

$$\begin{aligned}
 \text{treatment effect} = & (E[Y_{ist}|s = \textit{treated}, t = \textit{post}] - E[Y_{ist}|s = \textit{treated}, t = \textit{pre}]) \\
 & - (E[Y_{ist}|s = \textit{control}, t = \textit{post}] - E[Y_{ist}|s = \textit{control}, t = \textit{pre}])
 \end{aligned}
 \tag{1}$$

where Y_{ist} is the outcome of unit i in the group s at time t , *post* means the time after receiving the treatment, and *pre* means the time before the treatment. The difference-in-differences can rule

out the influences of neighborhood and community, natural environment, building-specific fixed features, consumer-specific fixed characteristics, and other unobserved time-invariant factors. To obtain a causal treatment effect, the parallel trend assumption is required between the treatment group and the control group to control for the influence of time-variant factors. I match treated houses with control houses at the county level for my national estimation (covering 23 states) and match at the city level for regional estimation. In most places of the U.S., the house property tax is calculated at the county level. I assume that the treated houses and control houses share a common macro time trend in the same county or city. I match at the county level for the national estimation to obtain observations covering as many areas across the U.S. as possible. Matching at the city level would generate more consistent treatment and control groups but it will remove more regions from my sample in the national analysis.

To justify the parallel trend assumption of my DID analysis, I regress the log of house prices on interaction terms between an indicator for being in the treatment group and the year of the transaction, controlling for county-by-year fixed effects, month-of-year fixed effects, property fixed effects, and building age using only pre-treatment data. The statistical results are shown in **Table 3.2** and **Figure 3.3**. I find that all the coefficients on the interaction terms are insignificant at a 5% level, which provides strong evidence that my model controls for time-variant unobservable differences across the treatment group and control group, consistent with the parallel trend assumption.

Table 3.2 Statistical results of interaction terms between treatment dummy and the year of the sale

Interaction terms between treatment dummy and the year of the sale	Coef.	Std. Err.	P-value
<i>T*Year2000</i>	0.090271	0.199177	0.65
<i>T*Year2001</i>	-0.04049	0.214139	0.85
<i>T*Year2002</i>	0.142318	0.21376	0.506
<i>T*Year2003</i>	-0.10501	0.205484	0.609
<i>T*Year2004</i>	0.081316	0.209301	0.698
<i>T*Year2005</i>	0.103851	0.202862	0.609
<i>T*Year2006</i>	0.096289	0.206167	0.64
<i>T*Year2007</i>	0.05221	0.203002	0.797
<i>T*Year2008</i>	0.177776	0.210701	0.399
<i>T*Year2009</i>	-0.03767	0.217235	0.862
<i>T*Year2010</i>	0.092223	0.209432	0.66
<i>T*Year2011</i>	0.01621	0.209909	0.938
<i>T*Year2012</i>	0.038587	0.206478	0.852
<i>T*Year2013</i>	-0.18201	0.204208	0.373
<i>T*Year2014</i>	-0.06648	0.196222	0.735
<i>T*Year2015</i>	0.090655	0.19696	0.645
<i>T*Year2016</i>	0.333574	0.199692	0.095

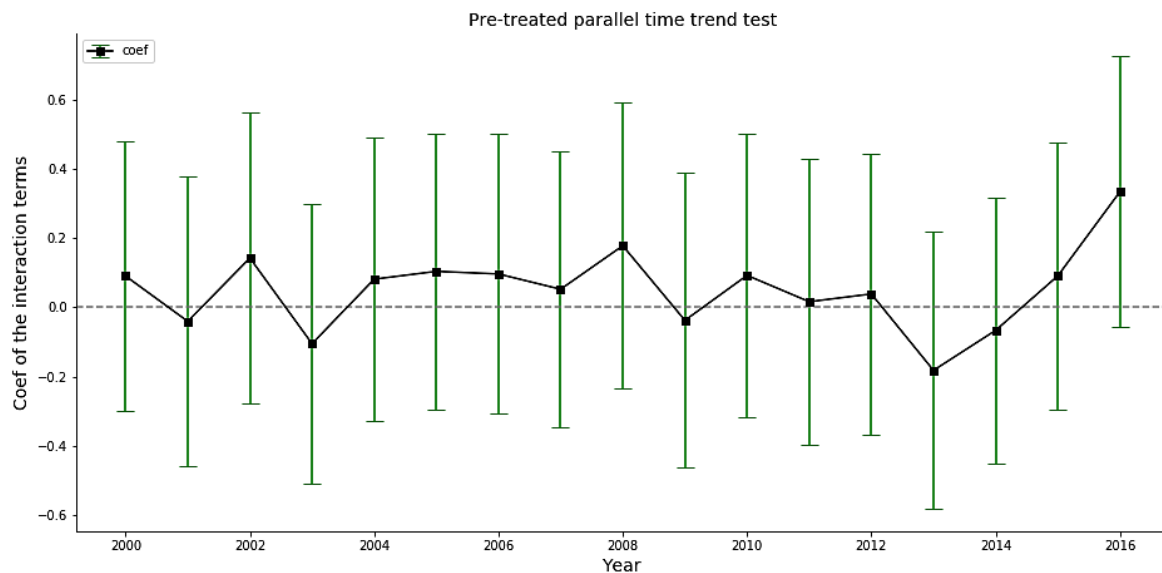


Figure 3.3 Pre-treatment trend test

Note: All the coefficients on the interaction terms except for the year 2016 are insignificant, which provides strong evidence that my model controls for time-variant unobservable

differences across the treatment group and control group. The green vertical line shows the 95% confidence interval.

For my baseline estimation model, I adopt the following two-way fixed-effect model, which can be regarded as a generalized DID model,

$$\ln Y_{ict} = \beta D_{it} + \alpha B_{it} + \delta V_{it} + \varphi_i + \sigma_c \cdot \vartheta_t + \mu_t + \varepsilon_{ict} \dots (2)$$

where $\ln Y_{ict}$ is the log of the sales price of house i at time t in county c . The price is converted into 2018 dollars adjusted for inflation rates. D_{it} is the treatment variable, which takes value one when house i has received the treatment (i.e., installed the heat pump) at time t . In my regression model, D_{it} takes value one only if house i is in the treatment group and the post-treatment period. φ_i controls individual fixed effects capturing all the time-invariant individual building-specific characteristics. $\sigma_c \cdot \vartheta_t$ is county-by-year fixed effects, which captures unobservable common features in each year of each county such as changing local housing market conditions. μ_t is month-of-year fixed effects, which absorbs variation over the annual cycle in the housing market. Moreover, B_{it} is the building age since it was built or remodeled (whichever is later). ε_{ict} is an idiosyncratic error term. I cluster my standard errors at the house level, allowing for arbitrary correlations between any two observations within the same house. Remodeling a house can significantly influence the house value. I can only observe the remodeling date for each house in my dataset but cannot observe the degree of remodeling. Thus, I remove the houses that were remodeled after the year 2000 from my sample to ensure no houses were remodeled between two transactions in my sample, which can help rule out the influence of remodeling on the estimation of the price premium. Houses remodeled after 2000 only account for a small portion

(4%) of my full sample. I further include a vector of control variables V_{it} to control for other time-variant factors, which are federal fund rates, demographic features by county level (Gallin, 2006), and the state-level prices of electricity and natural gas (Myers, 2019). These variables will be dropped when I include county-year fixed effects though I include these variables in other model specifications when the county-year fixed effects are not present. I obtain a robust causal effect of heat pump systems on house prices where there are no other unobservable time-variant differences between the control and treatment groups.

2.2.2 Cross-sectional data with nearest-neighbor matching

The DID approach relies on intertemporal price variation. However, the estimates would be biased if the hedonic gradient shifts over time (Kuminoff & Pope, 2014). To address this issue, I use an alternative approach that uses cross-sectional data in conjunction with the nearest neighbor matching technique following Muehlenbachs et al. (2015). To reduce the selection bias, I need to ensure both groups (treatment group and control group) are almost identical except for the treatment variable. The nearest neighbor matching is based on the Conditional Independence Assumption (CIA) (Angrist, 2008), which controls the selection bias conditional on observed features or covariates. However, the matching covariates in my dataset cannot cover all the house features. The DID is my preferred specification and the cross-sectional estimation with matching serves as a robustness check.

I first apply an exact match in the time dimension (transaction year) to control for unobservable time-variant factors and in the geographic dimension (city) to control for unobservable neighborhood factors. I then apply a propensity score matching to find the three nearest neighbors in the control group for each treated house based on the covariates of time-

invariant building characteristics (Qiu et al., 2017). The covariates for matching are the key house characteristics, including year built, number of stories, number of rooms, number of bedrooms, building area, and land assessed value. After the matching procedure, I run an OLS model by regressing the log of the house sale prices on a treatment dummy variable and the house feature covariates. The treatment dummy variable takes value one for treated houses and takes value zero otherwise. The coefficient of the treatment variable is my estimated treatment effect. The treatment effect estimated by cross-sectional data with matching (See the section 3.2) is consistent with the results of the DID approach.

I also conduct a robustness check by focusing on new buildings using the cross-sectional data. I still find a positive price premium, which is consistent with my baseline estimates (See the section 3.2).

2.2.3 The heterogeneity of the price premium

I explore the heterogeneity of the price premium by applying a flexible semi-parametric approach - partially linear varying coefficient fixed effects panel data model (Cai et al., 2017). This method allows for linearity in some variables and nonlinearity in other variables, where the effects of these regressors on the outcome variable vary based on low-dimensional variables nonparametrically (Cai et al., 2017), which has advantages in estimating non-linear heterogeneity. The model has been widely used (Lundberg et al., 2016; Delgado et al., 2014; Su et al., 2013). I adopt the following model

$$\ln Y_{it} = D_{it} \cdot g(U_{it}) + \beta V_{it} + \varphi_i + \vartheta_t + \mu_t + \varepsilon_{it}, \dots (3)$$

where Y_{it} is the sales price of house i at time t . U_{it} is a continuous variable of an influencing factor associated with the house i at time t . D_{it} is a treatment variable with functional coefficient $g(U_{it})$. V_{it} is a vector of control variables to control for other time-variant factors, which are federal fund rates, demographic features by county level, and the price of electricity and natural gas by state level. φ_i is individual fixed effects, ϑ_t is year fixed effects, and μ_t is month-of-year fixed effects. I use a linear combination of sieve basis functions to approximate the unknown functional coefficient $g(U_{it})$.

The historical data of federal fund rates were obtained from the online database of Macrotrends. The data of population density and personal income per capita by county was obtained from the Bureau of Economic Analysis, U.S. Department of Commerce. The data of monthly natural gas price and annual electricity price by the state were obtained from the U.S. Energy Information Administration. The data on residents' environmental awareness was obtained from the Yale Program on Climate Change Communication. The local adoption rate of air-source heat pumps by county was calculated based on ZTRAX data. The data for heating degree days and cooling degree days were obtained from the National Oceanic and Atmospheric Administration. The heating degree days and cooling degree days are computed based on a base temperature of 65 Fahrenheit degrees.

3. Results

3.1 House price premium induced by air-source heat pumps

I estimate the house sales price premium induced by air-source heat pumps using the DID approach with exact matching at the county level based on property data from the ZTRAX. The data includes two parts: building characteristics for each house in the U.S. from six assessments from 2016 to 2018, and historical transaction records across the U.S. The treatment group consists of houses which installed a heat pump. The control group consists of the houses using the same types of heating and cooling systems other than heat pumps across all the assessments and are sold at least twice during a similar data window. The transaction records in my final analysis are from 2000 to 2018 (not just during 2016-2018).

In my DID approach, I match treated houses and control houses in the same county. I remove the houses that were remodeled after the year 2000 (about 4% of the total sample) from my sample to exclude the influence of remodeling on the estimation of a price premium. I obtain 14,211 houses in the treatment group and 440,168 houses in the control group across the country covering 23 states.

I run a DID specification (two-way fixed effects model) to estimate the house sales price premium induced by heat pumps, by regressing the log of transaction prices on a dummy variable of installing a heat pump controlling for the building age, county-by-year fixed effects (or year fixed effects), month-of-year fixed effects, and individual property fixed effects to capture building, neighborhood, regional, and intertemporal confounding factors. Details of the sample restriction and DID modeling can be found in the section of data and methods. The coefficient of the heat pump installation dummy variable measures the average treatment effect on the treated (ATT).

Specifically, I compare 4 different model specifications. Results are shown in **Table 3.3**. In models 2 and 3, I include a vector of time-variant control variables, which are financial factors of monetary policies (Taylor, 2007), demographic features (Gallin, 2006), and the regional electricity

and natural gas prices (Myers, 2019). I obtain the historical data of federal fund rates, which plays an important role in influencing house prices, from the online database of Macrotrends. I obtain the data on population density, personal income per capita by county from 2005 to 2017 from the Bureau of Economic Analysis, U.S. Department of Commerce. I obtain the data on monthly natural gas prices by state from 1973 to 2019 and the data on annual electricity prices by state from 1990 to 2017 from the Energy Information Administration. Model 4 controls for county-by-year fixed effects and is my preferred model. Model 4 indicates that the estimated ATT is 7.1%, meaning that the installation of air source heat pumps induces a positive price premium, suggesting that houses with air-source heat pumps enjoy an additional 7.1% (or \$17,000) sales price premium on average compared to houses with other heating and cooling systems holding other factors fixed.

Table 3.3 The estimation results using the Difference-in-Differences approach

<i>Model</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>
<i>Coef. Of D (ATT, Price Premium)</i>	0.0511	0.0349	0.0625	0.0708
<i>P-value</i>	<0.001	<0.001	<0.001	<0.001
<i>Obs</i>	853,142	634,952	634,952	853,142
<i>Robust Std Err</i>	0.0069	0.0096	0.0102	0.011
<i>95% CI</i>	0.0374	0.0159	0.0424	0.0491
<i>95% CI</i>	0.0647	0.0538	0.0826	0.0924
<i>R-sq (overall)</i>	0.0483	0.0573	0.0027	0.018
<i>Groups/Houses</i>	440,764	378,267	378,267	440,764
<i>Building age control</i>	Yes	Yes	Yes	Yes
<i>Other time-variant control</i>	No	Yes	Yes	No
<i>Household fixed effects</i>	Yes	Yes	Yes	Yes
<i>Month-of-Year fixed effects</i>	Yes	Yes	Yes	Yes
<i>Year fixed effects</i>	Yes	Yes	No	No
<i>State-by-Year fixed effects</i>	No	No	Yes	No
<i>County-by-Year fixed effects</i>	No	No	No	Yes

* Standard errors are all clustered at the house level.

One caveat for my DID analysis is that I identify the treatment variable relying on differences in two records for the same property at different times. Heating type information may have been

missed out in the first recording. I address this concern from two perspectives. First, all the treated houses in my sample were sold within the following two years of the first assessment recording. There is unlikely any significantly systematic change in the recordings that may leave (or collect) a specific type of information during this short period. The sellers of the treated houses have a strong incentive to report the installation of a heat pump to increase the assessment value and ultimately the transaction price of their houses when the sellers know the houses will be on the market soon. Thus, it is unlikely to miss out on the heat pump information during the assessments, especially among the houses that are entering the market soon. Second, if the heat pump was missed out in some houses' first assessment recording, the price premium induced by the heat pump will be underestimated. The treatment group may include houses that were treated in both the pre-treated period and the post-treated period. Thus, including these houses in the treatment group underestimates the price premium, which still supports the main conclusion that the cost of installing an air-source heat pump can be recovered by the price premium.

I also apply another specification in the baseline DID model where remodeling and building age are included at the same time. I include a variable of building age (since a building was built) and an interaction term between the remodeling dummy and the variable of building age (since it was remodeled) in the baseline DID model. Results (coefficient: 0.148; standard error: 0.012) are consistent with my baseline estimation.

3.2 Robustness checks

I also apply several alternative econometric specifications for robustness checks.

First, I conduct robustness checks by allowing specific time trends for the treatment and control groups in my DID model, respectively, following the method conducted by Davis et al. (2014). I first conduct the same analysis as Davis et al. (2014) by adding interaction terms between the treatment group indicator variable and time trend variables (the number of years since 2000) into my baseline model. I estimated a linear time trend, quadratic time trend, and cubic time trend. The following equation (5) represents the above approach, while the equation (4) is my baseline DID model. These time trends can control for time-variant systematic differential trends between the treatment and the control groups. Following this approach, I further conduct additional analyses by adding the interaction terms between the county-by-group fixed-effects (here group indicates treatment group or control group) and the time trends in equation (6).

$$\ln Y_{ict} = \beta D_{it} + \alpha B_{it} + \delta V_{it} + \varphi_i + \sigma_c \cdot \vartheta_t + \mu_t + \varepsilon_{ict} \quad \dots(4)$$

$$\ln Y_{ict} = \beta D_{it} + \alpha B_{it} + \delta V_{it} + \varphi_i + \sigma_c \cdot \vartheta_t + \mu_t + \rho_1 T_i \cdot \gamma_t + \rho_2 T_i \cdot \gamma_t^2 + \rho_3 T_i \cdot \gamma_t^3 + \varepsilon_{ict} \quad (5)$$

$$\ln Y_{ict} = \beta D_{it} + \alpha B_{it} + \delta V_{it} + \varphi_i + \mu_t + \sum_{j=1}^2 \sum_{k=1}^c \tau_{jk} \cdot \gamma_t + \sum_{j=1}^2 \sum_{k=1}^c \tau_{jk} \cdot \gamma_t^2 +$$

$$\sum_{j=1}^2 \sum_{k=1}^c \tau_{jk} \cdot \gamma_t^3 + \varepsilon_{ict} \quad \dots(6)$$

where $\ln Y_{ict}$ is the log of the sales price of house i at time t in county c , D_{it} is the variable of heat pump adoption, B_{it} is the building age since it was built or remodeled (whichever is later), φ_i controls individual fixed effects, $\sigma_c \cdot \vartheta_t$ is county-by-year fixed effects, μ_t is month-of-year fixed effects, and ε_{ict} is the idiosyncratic error term. In equation (5), T_i is a treatment group indicator variable, which takes values one for buildings in the treatment group. γ_t is the number of years since 2000. In equation (6), τ_{jk} is the indicator dummy for buildings in group j (treatment group or control group) and county k . γ_t is the number of years since 2000.

Table 3.4 presents the estimation results. Column (1) is the baseline estimation result by equation (4) without time trend variables, Column (2)-(4) are the results by equation (5), while Column (5) is the result by equation (6). The results are relatively insensitive to including different time trends, suggesting that the uncontrolled time-varying confounding unobservables have little influence on my estimated treatment effect.

Table 3.4 The heat pump price premium estimation using the DID model with different time trends

Model	(1)	(2)	(3)	(4)	(5)
	<i>No time trend</i>	<i>Linear time trend</i>	<i>Quadratic time trend</i>	<i>Cubic time trend</i>	<i>Cubic time trend</i>
<i>Heat pump adoption</i>	0.07*** (0.011)	0.09*** (0.011)	0.08*** (0.011)	0.08*** (0.011)	0.07*** (0.008)
<i>Obs</i>	853142	853142	853142	853142	853142
<i>R-sq</i>	0.01	0.02	0.02	0.02	0.06
<i>Building age control</i>	Yes	Yes	Yes	Yes	Yes
<i>Household fixed effects</i>	Yes	Yes	Yes	Yes	Yes
<i>Month-of-Year fixed effects</i>	Yes	Yes	Yes	Yes	Yes
<i>County-by-year fixed effects</i>	Yes	Yes	Yes	Yes	No
<i>Treatment group dummy × linear time trends</i>	No	Yes	No	No	No
<i>Treatment group dummy × quadratic time trends</i>	No	No	Yes	No	No
<i>Treatment group dummy × cubic time trends</i>	No	No	No	Yes	No
<i>County-by-group fixed effects × cubic time trends</i>	No	No	No	No	Yes

* Standard errors are all clustered at house level and in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Second, I use the nearest neighbor matching technique based on cross-sectional data to conduct a robustness check. DID specifications rely on panel intertemporal variation and may fail to measure the slope of the hedonic function of price. The DID estimates could be biased if the hedonic gradient changes over time (Kuminoff & Pope, 2014; Muehlenbachs et al., 2015). To address this issue, I use the nearest neighbor matching technique based on cross-sectional data. I

first apply an exact match in the time dimension (transaction year) to control for unobservable time-variant factors and in the geographic dimension (city) to control for unobservable neighborhood factors. Then I apply a propensity score matching on the covariates of time-invariant building characteristics, which are correlated with house prices (Qiu et al., 2017; Case et al., 2004). The covariates for matching are the key house characteristics, including the year built, number of stories, number of rooms, number of bedrooms, building area, and land assessed value. After the matching procedure, I run OLS models to estimate the ATT. **Table 3.5** presents all the estimates of different specifications. The results in **Table 3.5** are consistent with my main results using the DID approach.

Table 3.5 Estimates using cross-sectional data with nearest neighbor matching

<i>Model</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>
<i>Coef. Of D (ATT, Price Premium)</i>	0.2131	0.1709	0.0278	0.2632	0.1501
<i>P-value</i>	<0.001	<0.001	<0.001	<0.001	<0.001
<i>Obs</i>	966,099	414,420	301,065	414,420	301,065
<i>Robust Std Err</i>	0.0043	0.0036	0.0043	0.0035	0.0042
<i>95% CI</i>	0.2047	0.1637	0.0193	0.2562	0.1417
<i>95% CI</i>	0.2216	0.1781	0.0362	0.2702	0.1584
<i>R-sq (overall)</i>	0.39	0.0053	0.07	0.26	0.30
<i>Groups/Houses</i>	966,099	414,420	301,065	414,420	301,065
<i>Matching</i>	No	Yes	Yes	Yes	Yes
<i>House features control</i>	Yes	No	Yes	No	Yes
<i>Year fixed effects</i>	Yes	No	No	Yes	Yes
<i>City fixed effects</i>	Yes	No	No	Yes	Yes

I also conduct a third robustness check by restricting the DID sample to transactions between 2016 and 2018, in order to directly control for the time-variant building features in my DID model (See data structure details in the section of data and methods). I match each transaction with the nearest assessment to approximate the building features when it was sold. To reduce the bias caused by frequent re-selling, I drop houses if the transaction interval is less than one year in the

control group. After these procedures, I obtain 428 treated houses and 4600 control houses covering 104 counties (including both treated and control houses) and 14 states. I further add the time-variant control variables of building features into the model, but only 117 treated houses are included in the model because of lacking building features for some houses.

Due to the small sample size, this estimation is vulnerable to a number of issues. First, the number of treated houses in each county is too small. In most cases, there are only 1-2 treated houses in a county. Second, the building features of six assessments do not reflect the actual building features when it was sold. Third, when I restrict the sample to a narrow time window (from 2016 to 2018), the question of frequent re-selling (“flapping”) will be raised. The house sales prices can be much higher or lower than market prices under the situation of frequent re-selling. **Table 3.6** presents the estimation results with and without control variables of time-variant building features. Despite the issues mentioned above, I still observe a price premium for the heat pump. The coefficient of the price premium is smaller and not significant after adding building feature control variables, which may be caused by the much smaller number of treated houses. The magnitude is also close to my main estimation result though the standard error differs due to the sample size.

Table 3.6 The price premium estimated by DID using the sample from 2016 to 2018

	(1)	(2)
Time periods	2000-2018	2016-2018
Price premium	0.071*** (0.011)	0.063 (0.081)
Building age control	Yes	Yes
Time-variant building features	No	Yes
Household FE	Yes	Yes
County by year FE	Yes	No
Year FE	No	Yes
Month of year FE	Yes	Yes
R square	0.009	0.063
Obs	440,764	4,984

*Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Time variant building features include the number of stories, number of rooms, number of bedrooms, number of bathrooms, and building condition level.

The last robustness check restricts the sample to new buildings. Focusing on new buildings can eliminate the confounding factors of contemporaneous building retrofits. I explore the possibility of using the new buildings subsample to provide additional analyses. I restrict my post-treatment analysis sample to only new buildings (in which the time interval between the year built and the first transaction is less than one year) and focus on the three states that have the highest number of heat pump homes (Georgia, Massachusetts, Virginia). This gives a sample of 1,751, among which 361 are heat pump homes. I run a simple hedonic regression model controlling for building features (e.g., number of stories, number of rooms, number of bedrooms, number of bathrooms, year built, building area, and the land assessed value per square feet.). The regression results are shown in **Table 3.7**. The results show a 0.175 coefficient for log(price), which is corresponding to 19.1% of price premium (when the coefficient is large, the percentage change is calculated as follows: the percentage change = $e^{\text{the estimated coefficient}} - 1$), which is consistent with my main results of a positive price premium. However, since the sample size is small and the cross-sectional analysis without a DID (there are no pre-heat-pump prices for new buildings) might

suffer from more unobservable confounding factors compared to the DID, I still prefer my DID results in my main discussions.

Table 3.7 The estimation using a cross-sectional analysis of new buildings

	(1) New buildings
Log(Price)	0.175* (0.102)
Building features control	Yes
County Fixed effects	Yes
R square	0.73
Obs	1,030

*Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controlled building features include the number of stories, number of rooms, number of bedrooms, number of bathrooms, year built, building area, and the land assessed value per square feet.

3.3 The lower bound of the price premium

Contemporaneous energy-efficiency and building upgrades may also be captured by the dummy variable of the heat pump in my model and cause the price premium to be overestimated. If these upgrades are counted as remodeling in the data, my results are unbiased because I dropped all houses remodeled after the year 2000. I conducted additional analyses to further eliminate the influence of contemporaneous upgrades. Specifically, I address these two concerns separately and calculate a lower bound of the housing price premium induced by air-source heat pumps.

3.3.1 Contemporaneous energy efficiency retrofits around the installation of a heat pump

I compare the installed energy efficiency measures of houses with heat pumps against houses without heat pumps. I conducted additional analyses and use the installation of an energy efficiency measure (a binary variable) as the dependent variable and whether the house has a heat pump (a dummy variable) as the independent variable based on a Probit model using all the

observations of Residential Energy Consumption Survey (RECS) data from Energy Information Administration (EIA), a nationally representative sample of residential consumers. I find that houses that installed heat pumps are more likely to have other energy-star qualified appliances compared to houses without heat pumps, but the marginally increased probabilities are small at about 10%-15%. I also find that there is no significant difference in installing a solar panel or a solar water heating system between the houses with and without heat pumps. The coefficient estimates and 95% confidence intervals of the Probit models are presented in **Figure 3.4** below.

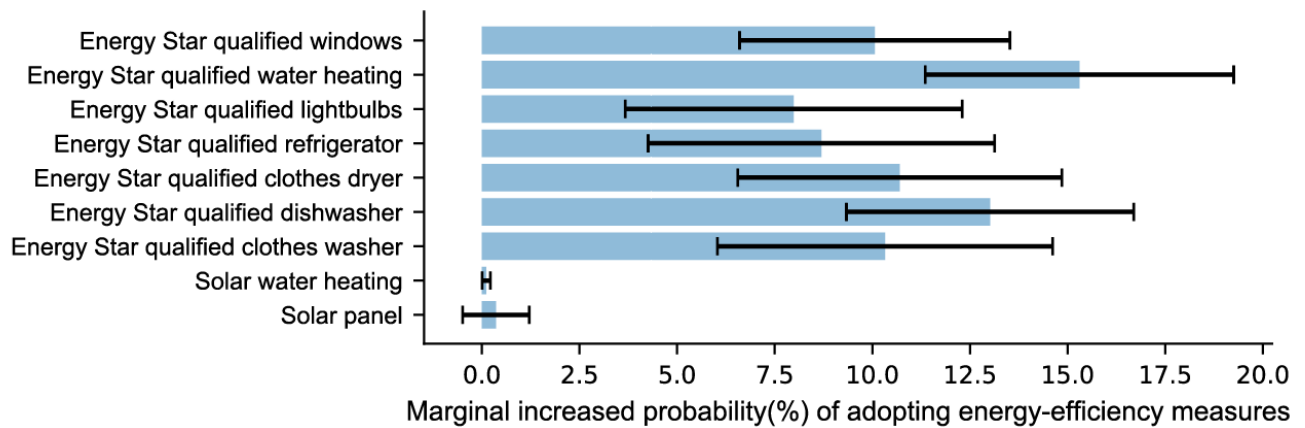


Figure 3.4 The adoption of energy efficiency measures of heat-pump houses against other houses.

I web scrape the price data of energy star qualified appliances from Home Depot online shopping site, and then use average prices as the value of these energy efficient appliances (See **Table 3.8**). I multiply the average prices of the energy star qualified measures by the estimated marginal increased probabilities and then subtract the sum of the products from the estimated price premium while calculating the lower bound. Consumers may overvalue or undervalue the energy efficiency measures in the housing market and the valuation based on online retail prices could be biased. In this essay, the calculated value of contemporaneous energy efficiency retrofits is very

limited (\$854) and it has limited influence on my major conclusion. Future studies with the data of energy efficiency measures at the individual building level can apply a hedonic model to directly estimate the value of these measures in the housing market.

Table 3.8 The average prices of energy-efficiency measures

Energy-efficiency Measures	Average price (\$)
Energy star qualified clothes washer	1700
Energy star qualified dishwasher	2890
Energy star qualified clothes dryer	600
Energy star qualified refrigerator	700
Energy star qualified water heating	700
Energy star qualified windows	700
Total	7290

3.3.2 Contemporaneous building retrofits/upgrades around the installation of heat pump

The potential correlation between the installation of heat pumps and other contemporaneous building upgrades may lead to a biased coefficient of the treatment dummy in the DID approach when upgrades are not properly controlled for. I have already removed the remodeled houses from my sample. In the lower bound analysis, I support my results with additional analyses and discussions.

Two potential different scenarios may introduce the correlation between heat-pump installations and other building upgrades. The first scenario is when the homeowners' primary purpose is to upgrade/retrofit their houses while installing an air-source heat pump as an addition. In this case, the building upgrade work is relatively large compared to the air-source heat pump. The second scenario is when the homeowners intend to install an air-source heat pump and the installation induces other building retrofitting work. The retrofitting is relatively small in this case because installing an air-source heat pump is easier.

In the first scenario, the propensity of upgrading a house (excluding energy-efficiency upgrading) between the treatment group and the control group should not be significantly different if the observed features between the two groups are balanced. As a result, I focus on the second scenario. I show that the building upgrading caused by the second scenario (caused by the adoption of heat pumps) is very small using additional housing characteristic data.

First, the DID approach controls for all the time-invariant confounding factors but not time-variant confounding factors. I conduct a pre-treated parallel trend test and find that there are parallel trends in house sales prices between the treatment group and the control group in the pre-treated period. Thus, I only focus on periods around the treatment (installation of heat pumps), which is within the periods of six assessments in my sample (2016 - 2018).

Next, I show that the major building features from 2016 to 2018 are overall balanced between the treatment group and the control group in my sample (see **Table 3.9**). I consider the following building features: the number of rooms, bathrooms, stories, bedrooms, building conditions, and building quality. A more stable, sounder, newer building at the time of assessment induces a higher building condition recording. Zillow database records six levels of building conditions for each property, which are “Unsound”, “Poor”, “Fair”, “Average”, “Good”, “Excellent.” I transform the building condition variable into an ordinal variable with six integers from 1 to 6. Better building materials, better interior decoration, and better building design induce a higher building quality recording. There are 15 levels of building quality for each property recorded by Zillow, which are from 1 to 15. Given the balanced features between the two groups, the propensity of building retrofits in the first scenario should not be systemically different between the treatment group and the control group. The balancing test cannot fully exclude unobservable differences between the treatment and control groups. The balancing test on observable variables provides suggestive

evidence on the properties of unobservable confounding factors (Davis and Wolfram, 2012; Ito, 2014). If I failed the balance test on the observables, the unobservable are more likely to be different across the treatment and control groups.

Table 3.9 The balance between treated houses and control houses in the sample of DID analysis

	<i>N. Of Stories</i>	<i>Total Rooms</i>	<i>Total Bedrooms</i>	<i>Total Bathrooms</i>	<i>Building Condition</i>	<i>Building Quality</i>
<i>Treated</i>	1.4921 (0.525)	6.4517 (1.770)	3.0852 (0.886)	2.3765 (0.808)	3.6034 (0.903)	9.4116 (2.327)
<i>Control</i>	1.4185 (0.544)	6.2692 (1.985)	3.1304 (0.910)	2.0577 (0.881)	3.5684 (0.840)	8.4671 (2.067)
<i>Obs</i>	425,717	257,365	390,581	394,479	321,275	321,275
<i>Balancing statistics:</i>						
<i>SMD</i>	0.138	0.097	0.050	0.377	0.040	0.429
<i>VR</i>	0.932	0.795	0.948	0.841	1.155	1.268

Notes: Standard deviations in parentheses. T-statistic is not used as the balancing statistic because it can mix up balance and sample size (Imai et al., 2008). Two other balancing statistics are used here to check the balance between the treatment and control groups in distributions and means, which have been widely used in the statistics research (Stuart et al., 2013). The first statistic is the standardized mean difference (SMD) aimed for comparing sample mean (Linden and Samuels, 2013). SMD is not influenced by sample size, which is defined as $SMD_j = \frac{|\bar{Y}_{jT} - \bar{Y}_{jC}|}{\sqrt{\frac{(s_{jT})^2 + (s_{jC})^2}{2}}}$, where Y_j is an attribute; S means the standard deviation; T and C denote treatment and control groups.

The second statistic is variance ratio (VR) aimed for comparing distribution, which is defined by Rubin (2001) as $VR_j = \frac{(s_{jT})^2}{(s_{jC})^2}$. According to Rubin (2001), when SMD is larger than 0.25, or VR is not within the range from 0.5 to 2, the treatment and control groups should not be balanced in means or distribution. According to these two statistics, I find the treatment and control groups in my sample are overall balanced, although the SMDs of the bathrooms and building quality is a little bigger larger than 0.25.

Third, I regress the dummy variable of heat pump adoption (takes value one if the heating types differ in two consecutive assessments and in the later assessment the heating type is a heat pump) on building feature changes using observations of six assessments from 2016 to 2018 including both treated and control houses in my DID analysis. **Table 3.10** presents the estimated results. All the coefficients are small in magnitude though still significant, potentially due to the

large sample size, indicating that the adoption of a heat pump entails a very small probability of other building retrofits. On average, the adoption of an air-source heat pump is correlated with an increase of 0.01 stories, 0.08 total rooms, 0.02 bedrooms, 0.04 bathrooms, 0.03 levels of building condition, 0.15 levels of building quality and 4% probability of changing roof cover (See **Table 3.10**). In rare cases, ducts need to be paved to transmit heat to different rooms under the roof of a house if a central air-source heat pump is installed. So, I also investigate the impact on the roof because the duct work may induce the house owner to retrofit the roof. My main conclusion still holds after accounting for these minor impacts (0.64% - 2.04% changes from the average building features).

Table 3.10 The impact of heat pump adoption on contemporaneous building feature changes.

	D. Stories	D. Total Rooms	D. Bedrooms	D. Bathrooms	D. Building Condition	D. Building Quality	Roof Cover Change
Heat Pump Adoption	0.0125*** (0.001)	0.0768*** (0.0035)	0.0201*** (0.001)	0.042*** (0.0015)	0.0347*** (0.005)	0.149*** (0.009)	0.0425*** (0.0015)
Obs	2,113,346	1,269,508	1,935,113	1,953,617	1,611,315	1,212,156	1,708,118
Average of the building feature	1.42	6.27	3.13	2.06	3.57	8.48	-
% change from average	0.88%	1.22%	0.64%	2.04%	0.97%	1.76%	-

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. “D. Stories”, “D. Total Rooms”, “D. Bedrooms”, “D. Bathrooms”, “D. Building condition”, “D. Building quality” are the first differences of the number of stories, total rooms, bedrooms, bathrooms and the levels of building condition and building quality between two consecutive assessments. There are six levels of building conditions for each property recorded by Zillow database, which are “Unsound”, “Poor”, “Average”, “Fair”, “Good”, “Excellent.” A more stable, sounder, newer building induces a higher building condition recording. I transform the building condition variable into an ordinal variable with six integers from 1 to 6. There are 15 levels of building quality for each property recorded by Zillow, which are from “E-” to “A+”. Better building materials, better interior decoration, and better building design induce a higher building quality recording. There are 22 categories of roof cover recorded by the Zillow database (e.g., Aluminum, Asphalt, Asbestos, Bermuda, Built Up, Concrete, Composition Shingle, Fiberglass, Gravel/rock, Gypsum, Metal, etc.) The variable of “roof cover change” takes value one if the roof cover types differ in two consecutive assessments. In rare cases, ducts need to be paved to transmit heat to different rooms under the roof of a house if a central air-source heat pump is installed. I investigate the impact on the roof because the ductwork may induce the house owner to retrofit the roof.

To further estimate the monetary value of these impacts, I apply a cross-sectional hedonic model by regressing the house prices on building features using the houses of control group and transactions from 2016 to 2018. The coefficients shown in **Table 3.11** are the unit monetary value (\$ in 2018) of the building features. I manually set the value of changing a roof cover to 20,000 dollars because it is hard to estimate the unit monetary value of the roof cover using the hedonic model given that the roof cover in Zillow data includes 22 categories. I multiply the unit monetary value of the building features by the estimated marginal increase of building features caused by the heat pump. I then subtract the sum of the products from the estimated price premium when calculating the lower bound.

In total, I subtract the value of contemporaneous energy efficiency retrofits (\$854.0) and the value of contemporaneous building retrofits (5,902.0\$) from the estimated price premium (\$17,162.4) and obtain a lower bound of the price premium (\$10,406.4). The ATT of 7.1% (\$17,162.4) in the last section can be treated as an upper bound.

My approach of subtracting the impact of other contemporaneous projects is similar to Finkelstein et al. (2012), which subtracts the impact of other potentially correlated welfare programs when analyzing the impact of the Medicaid program.

Table 3.11 The hedonic model using control houses from 2016 to 2018

	<i>Coef.</i>	<i>Std. Err.</i>	<i>P value</i>
<i>N. Of Stories</i>	4118.762	1410.502	<0.01
<i>Total Rooms</i>	5489.311	553.33	<0.01
<i>Total Bedrooms</i>	-5783.821	863.02	<0.01
<i>Total Bathrooms</i>	29310.7	1011.03	<0.01
<i>Building Condition</i>	11997.16	810.63	<0.01
<i>Building Quality</i>	20318.78	549.4	<0.01
<i>Area</i>	16.72	0.305	<0.01
<i>Pool</i>	55995.14	4713.54	<0.01
<i>Good site</i>	47720.96	3931.06	<0.01
<i>Building Age</i>	147.35	18.97	<0.01
<i>Year FE</i>		Yes	
<i>County FE</i>		Yes	
<i>R square</i>		0.48	
<i>Obs</i>		54,562	

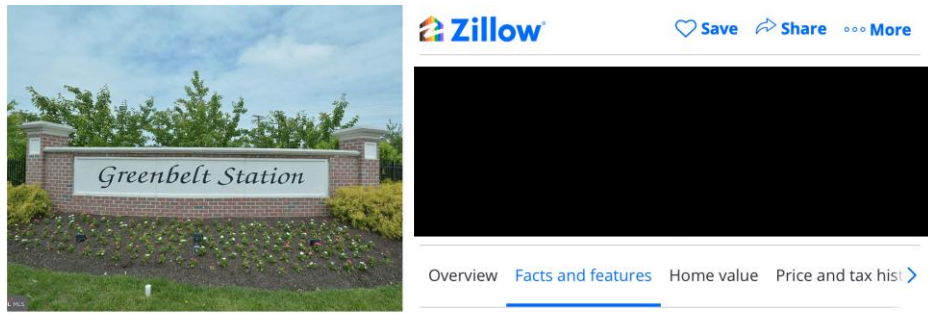
*Notes: Because the six assessments are from 2016 to 2018, I restrict the sample to transactions from 2016 and 2018. I match each transaction with the nearest assessment to approximate the building features when it was sold. Because the houses in my sample were not remodeled, the building features of the area, pool, good site are time-invariant. Thus, I do not include these features while estimating the impact of heat pump adoption on building retrofits. “Good site” is a dummy variable, which takes value one if the building is close to a school, airport, railway station, major street, lake, ocean, or green belt. “Pool” is a dummy variable, which takes value one if the building has a swimming pool.

3.3.3 The comprehensiveness of building features considered

Below I show that all the important contemporaneous building upgrades from Zillow that can influence house sales prices are accounted for in my analyses.

Figure 3.5 presents all the categories of the “Facts and features” of homes shown to house buyers on the Zillow website when they are comparing different houses. These features of houses are the major information that house buyers can receive when they search for a house, and also the major indicators for house buyers to compare different comparable houses. Thus, these categories of features can be regarded as the major building-feature factors that influence the house sales price.

The building features shown in **Figure 3.5** include building age, heating and cooling systems, building area, parking space, the number of rooms/bathrooms/bedrooms/stories, appliances (including energy star qualified appliances), flooring, home type, architectural style, construction material information. In my paper, I take all of these building features into account. First, I remove the buildings with remodeling after 2000 from my sample, so the building area, architectural style, swimming pool, parking space and construction material would not change in my sample. Second, I take all the other features into account in my lower bound analysis. I also include the levels of building condition and building quality into my model. A more stable, sounder, newer, cleaner building at the time of assessment induces a higher building condition recording. Zillow database records six levels of building conditions for each property, which are “Unsound”, “Poor”, “Fair”, “Average”, “Good”, “Excellent.” Better building materials, better interior decoration, and better building design can be reflected in (and thus controlled for by) a higher building quality indicator. There are 15 levels of building quality for each property recorded by Zillow, which are from “E-” to “A+”. See **Figure 3.6** for the detailed description of the building condition and building quality variables, which can control for a very comprehensive set of building characteristics.



Facts and features

Type:	Single Family	Parking:	1 space
Year built:	2016	HOA:	\$292/month
Heating:	Forced air	Lot:	1,225 sqft
Cooling:	Central	Price/sqft:	\$156

Interior details

Bedrooms and bathrooms

- Bedrooms: 3
- Bathrooms: 3
- Full bathrooms: 2
- 3/4 bathrooms: 0
- 1/2 bathrooms: 1
- 1/4 bathrooms: 0

Appliances

- Appliances included: Dishwasher, Refrigerator, Disposal, Microwave, Washer/Dryer Stacked, Self Cleaning Oven, Stainless Steel Appliance(s), Bar Fridge

Flooring

- Flooring: Hardwood

Other interior features

Interior details

Bedrooms and bathrooms

- Bedrooms: 3
- Bathrooms: 3
- Full bathrooms: 2
- 3/4 bathrooms: 0
- 1/2 bathrooms: 1
- 1/4 bathrooms: 0

Flooring

- Flooring: Hardwood

Heating

- Heating features: Forced Air, ENERGY STAR Qualified Equipment, Programmable Thermostat

Cooling

- Cooling features: Central Air, ENERGY STAR Qualified Equipment, Programmable Thermostat

Appliances

- Appliances included: Dishwasher, Refrigerator, Disposal, Microwave, Washer/Dryer Stacked, Self Cleaning Oven, Stainless Steel Appliance(s), Bar Fridge

Other interior features

- Total interior livable area: 2,600 sqft
- Finished area below ground: 0 sqft
- Fireplace: Yes
- Virtual tour: [View virtual tour](#)

Property details

Parking

- Parking features: Attached Garage, Garage Door Opener, Garage Faces Rear
- Garage spaces: 1
- Covered spaces: 1
- Attached garage: Yes

Property

- Stories: 2
- Exterior features: Brick, Vinyl
- Lot size: 0.03 acres

Other property information

- Parcel number: 215581946

Construction details

Type and style

- Home type: Single Family
- Architectural style: Colonial

Material information

- Construction materials: Vinyl Siding, Brick

Condition

- New construction: No
- Year built: 2016

Figure 3.5 The “Facts and features” of homes showed on the Zillow website

Note: These figures are obtained from the website: https://www.zillow.com/homes/for_sale/

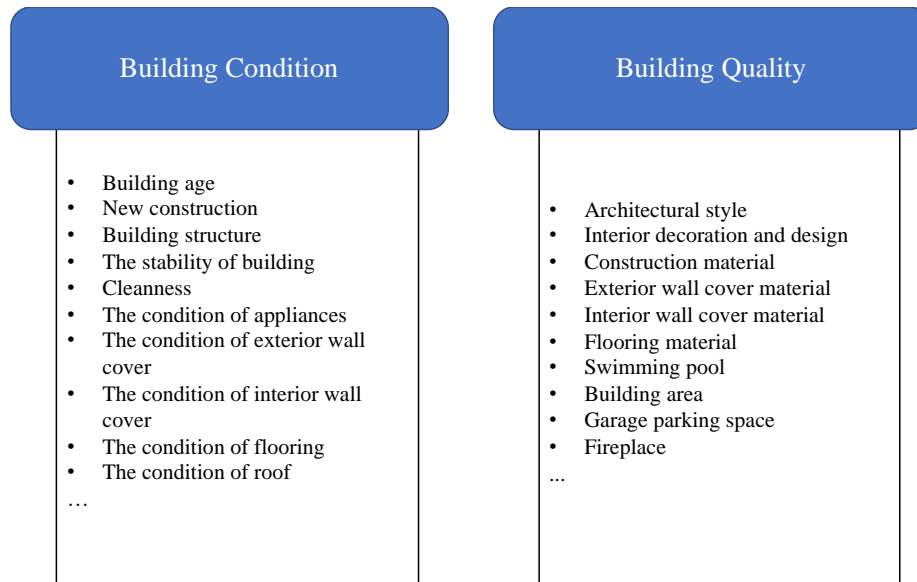


Figure 3.6 The attributes in the indicators of building condition and building quality recorded by Zillow

In addition, the building condition indicator reflects the maintenance level of the buildings and addresses the concern about the systematic difference in house owners between the heat-pump houses and other houses. The owners of “green” homes may differ from owners of conventional homes and also take better care of that home. In this situation, the adoption of heat pumps could be correlated with the improved maintenance level of the homes made by the “green” homeowners. To address this concern, I account for potential contemporaneous better building maintenance around the same time of the heat-pump adoption using the variable of building condition indicator. I then subtract the marginal value of these contemporaneous upgrades from my estimated heat-pump house price premium in my lower bound analysis.

3.4 The heterogeneity of the price premium

The house sales price premium induced by air-source heat pumps may differ across different regions and demographic groups. I examine the heterogeneity of the price premium by

investigating the correlation of the price premium to several other important factors, including residents' environmental awareness at the county level, air-source heat pump adoption rate at the county level, personal income per capita at the county level, average annual heating degree days, and annual cooling degree days (Mense, 2017) from 1981 to 2010 at the meteorological station level. I use the percentage of people who believe global warming is happening in a county to measure the residents' environmental awareness, based on the Yale Program on Climate Change Communication (Howe et al., 2015). All of the above factors are not strongly correlated to each other except for heating degree days and cooling degree days (See **Appendix A**).

I apply a flexible semi-parametric approach using the partially linear varying coefficient fixed effects panel data model. This approach allows for linearity in some variables and nonlinearity in other variables, where the effects of these regressors on the outcome variable vary based on low-dimensional variables nonparametrically (Cai et al., 2017), which shows advantages in estimating non-linear heterogeneity. See the details of model specifications in the section of data and methods.

Figure 3.7 shows the estimated relationships between the price premium and other factors. I find that residents who are environmentally conscious, or middle class, or live in regions with a mild climate are most likely to pay a higher price premium for houses with air-source heat pumps. The price premium induced by heat pumps is not statistically significant for people in regions with too low or too high levels of environmental awareness, heat pump penetration rate, income, heating degree days and cooling degree days. When residents care more about the environment, they are more willing to pay extra money for the “environmental-friendly” air-source heat pumps. However, as environmental awareness further increases, residents may favor other green technologies such as solar panels, home energy storage, and electric vehicle that are more visible to others to show

the environmental status of the owners. This leads to noises in the price premium when environmental awareness is high. The insignificant and lower price premium when the penetration rate is very low can be explained by uncertainty in the adoption of novel technologies. During the very early stage of technology adoption, consumers have little knowledge about how to use the technology, its performance, and future return (Strong, 2019). In this case, consumers tend to observe the behavior of another person who has used the novel product to infer the usefulness of this product (Walden & Browne, 2009; Mulder et al., 2003). Thus, the first user will have much less incentive to adopt the new product (Gillingham & Palmer, 2014), which leads to a lower/insignificant price premium when the penetration rate is very low. For the downward trend when the penetration rate is larger, the lower house price premium could be due to lower installation costs, information searching costs, and transaction costs with the increase of penetration rate (See the detailed explanation in **Appendix A**). The relationship between the price premium, heating degree days, and cooling degree days is consistent with the physics of heat pumps (See the detailed explanation in **Appendix A**). When the income level is low, households cannot afford to upgrade their homes, which leads to an insignificant price premium. High-income households may spend a large amount of money on other house retrofits. Thus, homebuyers will pay more attention to these other distinguished and salient house features, and the heat pump will be overlooked among high income residents.

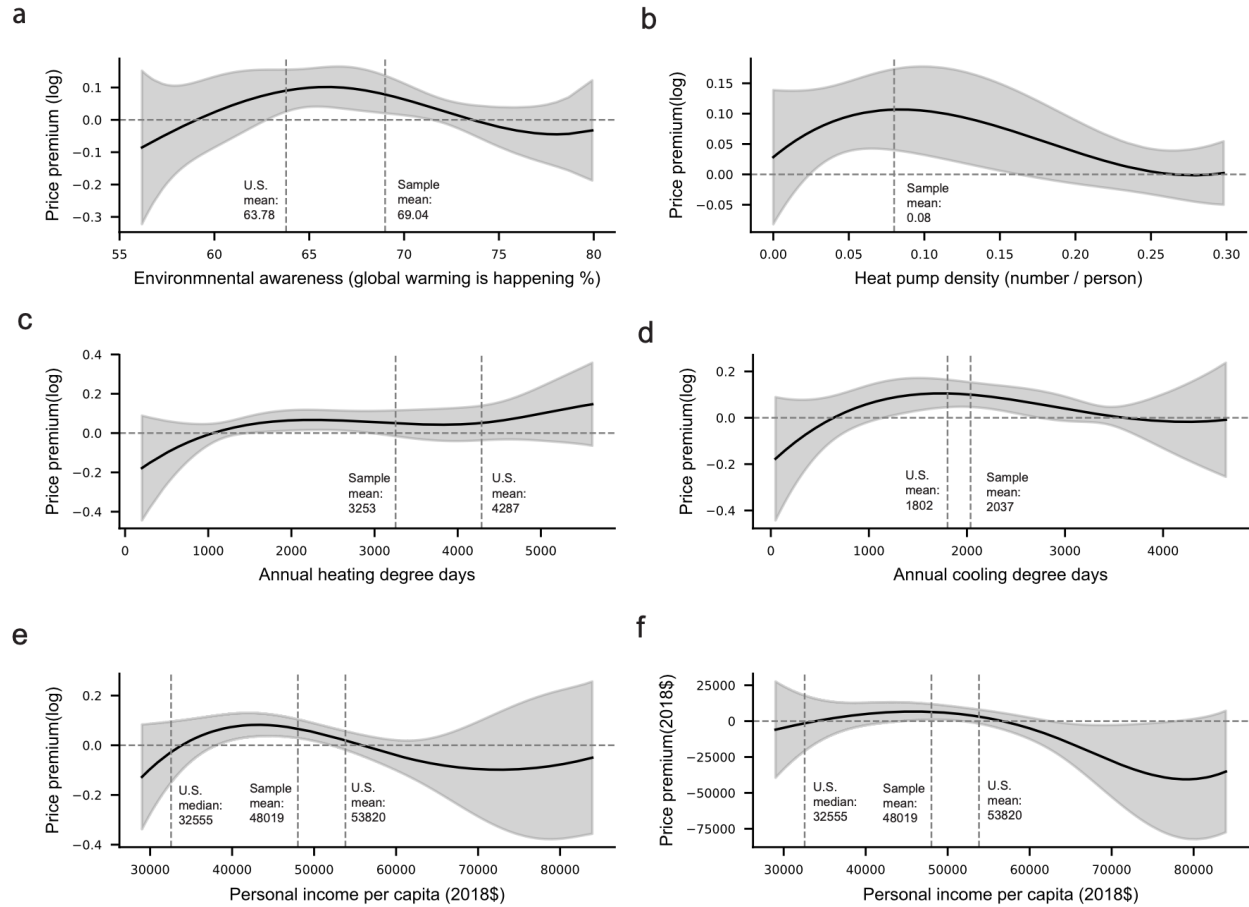


Figure 3.7 The heterogeneity of the price premium induced by air-source heat pumps.

Note: a, The relationship between the price premium and residents' environmental awareness. I use the percentage of people who believe global warming is happening in a county to measure the residents' environmental awareness, based on the Yale Program on Climate Change Communication. b, The relationship between the price premium and heat pump penetration rate. c, The relationship between the price premium and annual heating degree days. d, The relationship between the price premium and annual cooling degree days. e, The relationship between the price premium (%) and personal income per capita (2018\$). f, The relationship between the price premium (2018\$) and personal income per capita (2018\$). I fit these curves based on a partially linear varying coefficient fixed effects panel data model. Gray shaded area means 95% confidence intervals.

Since the house prices are higher among high income residents, the percentage of the price premium induced by heat pumps will be diluted by the high house price if I use the log of price as the outcome variable. Thus, I also use the absolute price as the outcome variable and delete the observations with the top 1% and bottom 1% sales prices to reduce the influences by extreme

values. I re-run the model and find that the new estimated relationship is consistent with my previous findings (See **Figure 3.7** (e) and (f)). The price premium still declines when the income level increases above the average level and the inverted “U” relationship still holds.

Residents’ environmental awareness can also be related to political affiliation or racial background. Due to the data limitation and the scope of the paper, I only explore the correlation between the price premium with other factors. While my research only demonstrates the potential correlation, future research can explore the causal mechanism channels (e.g., through political affiliation, demographics) that impact the willingness to pay for the heat pump.

I also conduct a robustness check using a traditional method based on interaction terms between the treatment variable and a set of dummies for different quantiles of the distribution of other influencing factors. **Supplementary Table 1** in **Appendix A** shows the estimated results, which are consistent with the results using the partially linear varying coefficient model.

3.5 The geographical distribution of the price premium

In addition to national estimations (across 23 states), I also provide regional estimates on the house price premium caused by heat pump adoption.

According to U.S. Census Bureau, the U.S. is divided into 9 divisions: New England (States: ME VT NH MA RI CT), Middle Atlantic (States: NJ NY PA), East North Central (States: IL IN MI OH WI), West North Central (States: IA KS MN MO NE ND SD), South Atlantic (States: DE DC FL GA MD NC SC VA WV), East South Central (States: AL KY MS TN), West South Central (States: AR LA OK TX), Mountain (States: AZ NM CO UT WY ID MT NV), Pacific (States: AK CA HI OR WA).

The number of treated observations in my DID specification is too small to provide a precise estimation in seven of the nine census divisions. **Table 3.12** shows the sample size under the DID specification for each census division.

Table 3.12 Sample size under the DID specification for each census division.

	<i>Treated houses</i>	<i>Control houses</i>
<i>New England</i>	28	848
<i>Middle Atlantic</i>	164	29072
<i>East North Central</i>	97	28038
<i>West North Central</i>	111	47541
<i>South Atlantic</i>	11912	156387
<i>East South Central</i>	132	3501
<i>West South Central</i>	44	22917
<i>Mountain</i>	52	50825
<i>Pacific</i>	1671	101039

Thus, I could only provide a precise estimate for the divisions of South Atlantic and Pacific, which have large enough treated observations. I match the treated buildings with control buildings at city level. I run the same econometric model as model 4 in **Table 3.3** by census division level to obtain the regional overall price premium induced by the heat pump. I control the building age since it was built or remodeled and include month-of-year fixed effects and county-by-year fixed effects. The standard errors are clustered at the house level. **Table 3.13** presents the estimates using the DID approach for Pacific and South Atlantic.

Table 3.13 Estimates using DID approach in the division of Pacific and South Atlantic

<i>Division</i>	<i>Coef. Of D</i>	<i>P-value</i>	<i>Obs</i>	<i>Robust Std Err</i>	<i>95% CI</i>	<i>95% CI</i>	<i>R-sq</i>
<i>South Atlantic</i>	0.064	<0.001	266,585	0.0121	0.0405	0.0882	0.0374
<i>Pacific</i>	0.052	0.064	174,910	0.02836	-0.00298	0.1082	0.0161

I also estimate the lower bound price premium in the Pacific and South Atlantic regions. I assume that the value of contemporaneous energy efficiency retrofits and contemporaneous building retrofits is the same across the country, so I subtract 6,756\$ from the price premium in Pacific and South Atlantic to obtain a lower bound price premium in these two census divisions.

In addition, I apply an alternative approach to estimating regional price premium using the cross-sectional data (post-treatment data) with nearest neighbor matching. In the post-treatment dataset, I have enough observations for all the divisions to provide precise estimation, but the cross-sectional data suffers from unobservable confounding factors. Thus, I only use the estimates using post-treatment data as a robustness check. **Table 3.14** shows the estimates for all the divisions. I run the same models as model 5 in **Table 3.5**. I regress the log of the house sales price on a treatment dummy controlling for house features, city fixed effects, transaction year fixed effects after matching. The estimates in Pacific and South Atlantic are consistent with the above DID estimates.

Table 3.14 Estimates using post-treatment data with nearest neighbor matching

<i>Division</i>	<i>Coef. Of D</i>	<i>P-value</i>	<i>Obs</i>	<i>StdErr</i>	<i>95% CI</i>	<i>95% CI</i>	<i>R-sq</i>
<i>New England</i>	0.2098207	<0.001	2,438	.0291278	.1527024	.2669391	0.5006
<i>Middle Atlantic</i>	0.0306784	0.010	19,108	.011864	.0074232	.0539336	0.3132
<i>East North Central</i>	0.1242622	<0.001	14,809	.014995	.0948702	.1536543	0.2423
<i>West North Central</i>	0.4149243	<0.001	3,807	.0423057	.33198	.4978686	0.3823
<i>South Atlantic</i>	0.1040034	<0.001	207,132	.0053658	.0934864	.1145203	0.3061
<i>East South Central</i>	0.3601161	<0.001	2,996	.0426187	.276550	.4436814	0.3369
<i>West South Central</i>	0.3115806	<0.001	4,385	.0359909	.2410199	.3821412	0.3435
<i>Mountain</i>	1.642825	<0.001	2,414	.0941124	1.458274	1.827375	0.2993
<i>Pacific</i>	0.2544903	<0.001	43,976	.0095059	.2358584	.2731221	0.2807

4. Discussion and conclusion

In this study, I provide empirical evidence about the effect of air-source heat pump adoption on residential property values. Houses with an air-source heat pump enjoy a 4.3%-7.1% (\$10,400 - \$17,000) sales price premium on average in 23 states of the U.S.

To better understand the estimated price premium, I compare the price premium with the installation cost of an air-source heat pump, and the additional cost and the net benefit of replacing a traditional HVAC system with an air-source heat pump. The net benefit includes lifetime fuel cost saving and lifetime avoided environmental damage, including reduced emissions of CO₂ and other hazardous pollutants. See the estimation process of the cost and benefit in **Appendix B**. I make these comparisons in two regions (census divisions of South Atlantic and Pacific) as I can only provide precise estimates on the price premium for the divisions of South Atlantic and Pacific with enough observations for the DID approach (See section 3.4).

I find that, in both Pacific and South Atlantic, the upper bound of price premium (\$15,400 and \$16,200, respectively) and the lower bound of price premium (\$8,644 and \$9,444, respectively) are larger than the average installation cost of an air-source heat pump (the average installation cost is about \$8,000). The additional cost is close to the lifetime fuel cost saving (\$2,948 and \$3,583, respectively) as well as the total net benefit (\$3,017 and \$3,965, respectively) associated with a switch from a traditional HVAC system to an air-source heat pump. **Figure 3.8** presents these comparisons.

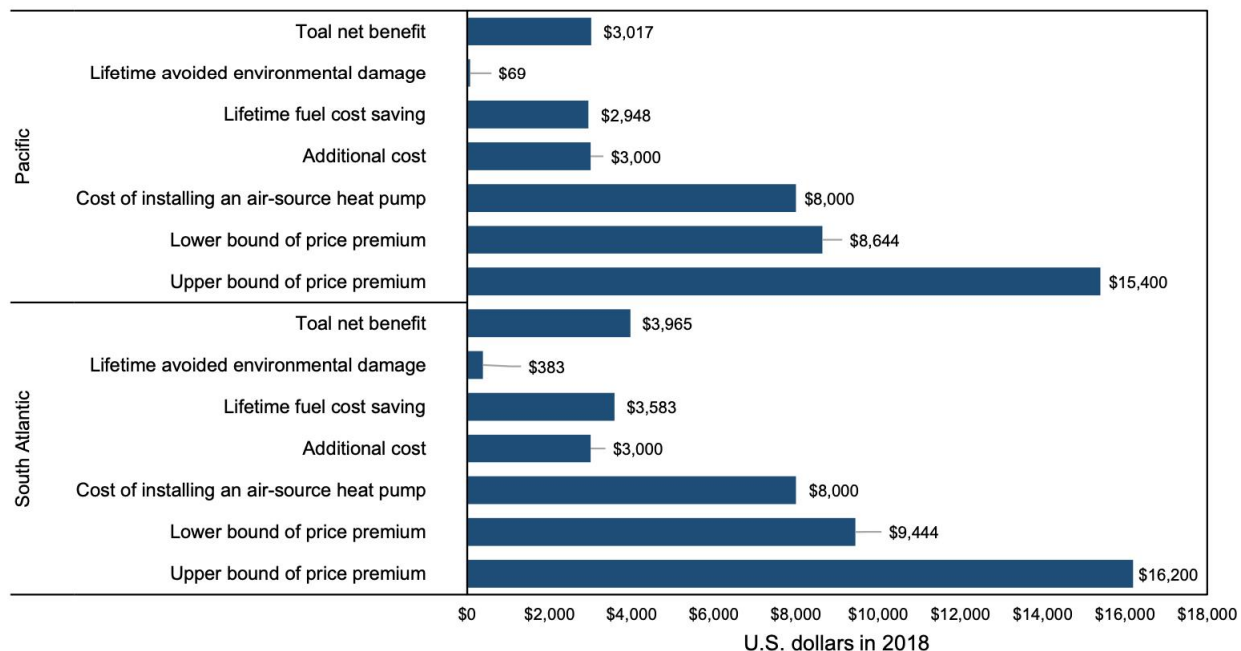


Figure 3.8 Comparing the price premium with the cost and benefit of replacing a traditional HVAC system with an air-source heat pump.

Note: This figure plots the lifetime fuel cost saving, lifetime avoided environmental damage, the total net benefit of switching to an air-source heat pump from a traditional HVAC system with current power grid; the additional cost (extra cost of installing an air-source heat pump compared to a traditional HVAC system); the cost of installing an air-source heat pump; and the house price premium induced by air-source heat pumps. (unit: Dollars in 2018) The cost of installing an air-source heat pump and a traditional HVAC system depends on the size of the home and type of equipment. The cost of installing an air-source heat pump typically ranges from 4000 to 12000 dollars. The cost of installing a traditional HVAC system typically ranges from 3000 to 7000 dollars. The extra cost of installing an air-source heat pump compared to an HVAC system is about 3000 dollars. The Upper bound of the price premium is directly estimated from the DID model. Lower bound of the price premium is the upper bound minus the product of the values of contemporaneous energy efficiency and building upgrades and the probability of conducting these other upgrades together with installing heat pumps.

The relatively high price premium (compared to the installation cost) can be explained by the transaction cost, information searching cost, and cognitive cost. In an equilibrium re-sale market, the house price premium approximates the sum of installation cost, transaction cost, information searching cost, and cognitive cost. If the house price premium is larger than the sum

of these costs, people will buy a house without heat pumps and install one by themselves when I assume that the value of dismantled old HVAC equipment is close to zero. First, a resident may be willing to pay to avoid complications such as removing the old heating system, doing necessary upgrade work, and having to wait at home for the complete installation work (all of which can be thought of as transaction costs) (Gillingham & Palmer, 2014). These costs, including the opportunity cost of lost time, can be quite high for some homeowners or certain types of houses (or certain existing heating systems). Moreover, given the low penetration rate of heat pumps, inexperienced installers may increase the time, cost, and risk of installation, (Bollinger & Gillingham, 2014; Gillingham et al., 2016) contributing to even higher transaction costs. Second, there are information searching costs (Gillingham et al., 2016) for consumers who need to spend time and effort to gather and compare different information about the price and performance of heat pumps between different installers. Currently, there is no one-size-fits-all heat pump in the U.S. The costs and capacity needed for different homes vary. It is not straightforward to obtain the price information of heat pumps for a specific building, since a good estimate may require the installer to visit the home. Third, there are cognitive costs for consumers who need knowledge literacy and to spend efforts to understand a new technology (e.g., heat pumps) and the financial aspects (upfront cost versus future benefits), and then make a decision to adopt it. Complex information may impede some consumers' understanding and rational behavior (Houde, 2018; Ito, 2014). Literacy could be a significant determinant of investment in energy efficiency (Brent & Ward, 2018). For some consumers, they may not think of the option of heat pumps when their HVAC systems are broken and need to be replaced.

The divergence between the installation cost and house price premiums is also observed for other energy technologies using housing characteristics and transaction data. For example, two

recent studies (Qiu et al., 2017; Dastrup et al., 2012) find a positive house sales price premium induced by solar panels ranging from \$23,000 to \$28,000 in 2012 and 2014. This price premium is also larger than the installation cost of solar panels, which is \$14,400 for an average-sized 3.6-kW PV system in 2014 (Barbose et al., 2018).

Figure 3.8 shows that the lifetime fuel cost savings associated with a heat pump compared to a traditional HVAC system are large enough to compensate homeowners for the additional cost of installing an air-source heat pump, and the house re-sale price premium is large enough to compensate the installation cost of the heat pump. Nonetheless, the penetration rate of air-source heat pumps in the U.S. is still small. There may be several explanations for this “energy efficiency gap”. First, most home buyers do not know whether and when they will sell their homes in the future. Uncertainties can lower house owners/buyers’ willingness (Qiu et al., 2014) to adopt new energy technologies. Second, imperfect and asymmetric information (Gillingham & Palmer, 2014) about the benefits of heat pumps could impede the adoption. Third, liquidity constraints also matter given that the median American household only has about \$12k in savings (CNBC, 2018). Fourth, a heat pump may not be attractive for some consumers (such as for homes without new or robust electrical wiring, or households who do not use space heating and cooling very often) even it is attractive for the average consumer given the “consumer heterogeneity” (Allcott & Greenstone, 2012).

Nevertheless, my results show that the value of the heat pump is recognized by the housing market and home buyers. My estimated price premium is larger than the cost of installing an air source heat pump, which is valuable information for homeowners who are deciding whether to install heat pumps. A significant positive price premium reduces consumer risk of not being able to recover their investments when selling their houses (Qiu et al., 2014). This is an important

contribution to the literature on the “energy efficiency gap”, where studies typically compare fuel cost savings to the initial cost of installation. The significant positive house price premium is an important incentive for energy efficiency investment. Policymakers can use the information about potential price premiums to influence consumer choices, in addition to traditional energy guides, which typically focus on fuel costs. For instance, the government or other authorities put a certified “energy-efficient heat pump” label on homes with heat pumps to encourage adoption.

Many nations, states, and cities have introduced decarbonization plans relying on the conversion to heat pumps as discussed earlier in the introduction. Given the increasing importance of electrification, my study adds a new dimension to quantify the benefit of installing heat pumps. There are significant house price premiums and net social benefits associated with a switch to heat pumps in the Pacific and South Atlantic regions of the United States. Similar analyses should be conducted in other countries with the urgent need for space heating electrification.

Three types of factors can influence the full social benefits of heat pumps, including the net fuel cost savings and net environmental savings associated with the electrification of space heating and cooling, the evolution of the electric grid in the future, and other potential benefits associated with the heat pump. More studies are needed to systematically quantify the social benefits of switching to heat pumps to better assist policymaking.

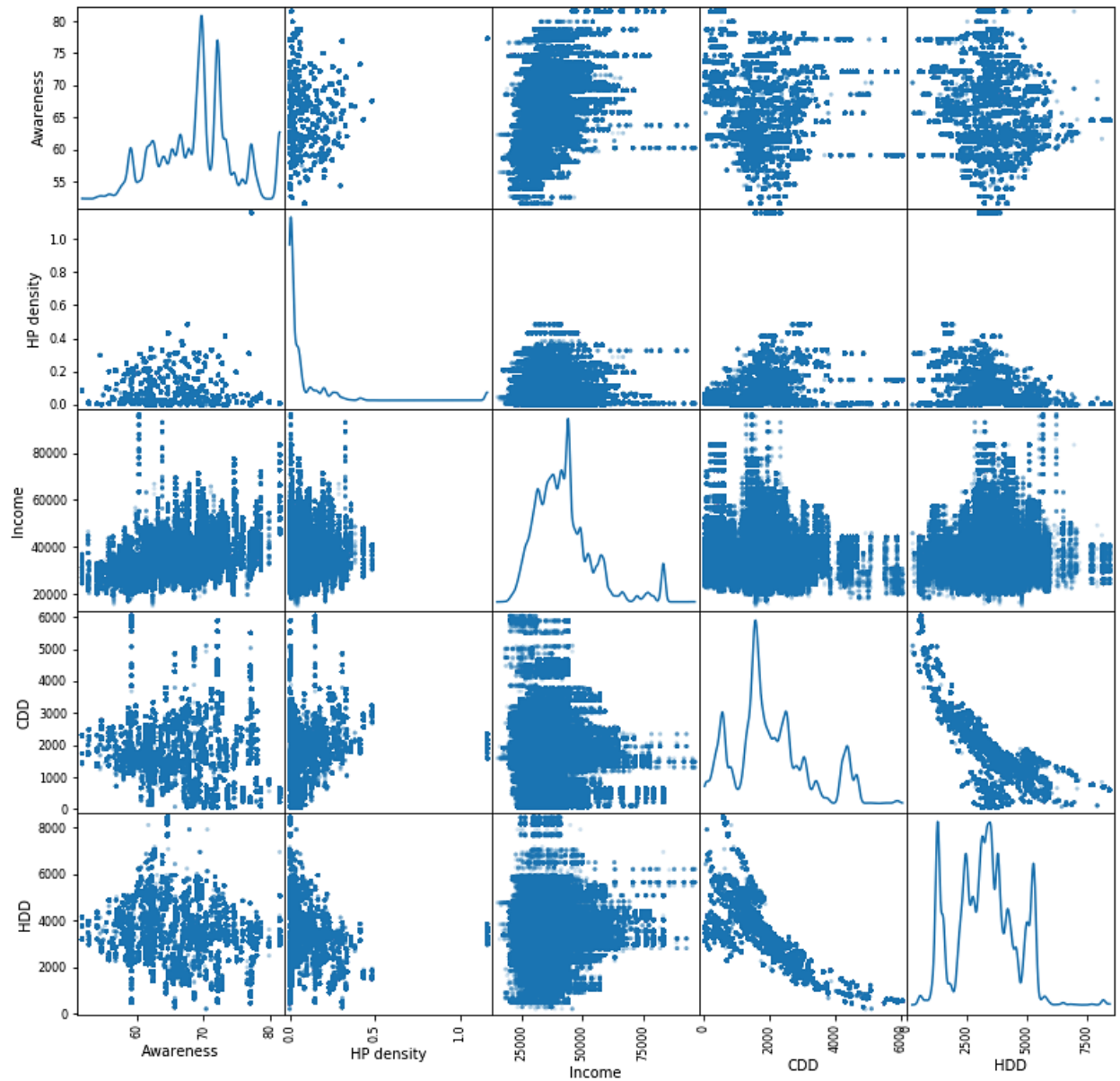
Appendix

Appendix A. The heterogeneity of the price premium induced by air-source heat pumps

I explore the heterogeneity of the price premium by investigating the correlation of the price premium to a number of factors (residents' environmental awareness at the county level, air-source heat pump adoption rate at the county level, personal income per capita at the county level, average annual heating degree days and annual cooling degree days from 1981 to 2010 at the meteorological station level).

(1) The correlation between the factors

These factors are not strongly related to each other except for heating degree days and cooling degree days (See **Supplementary Figure 1**).



Supplementary Figure 1. The correlation between investigated factors

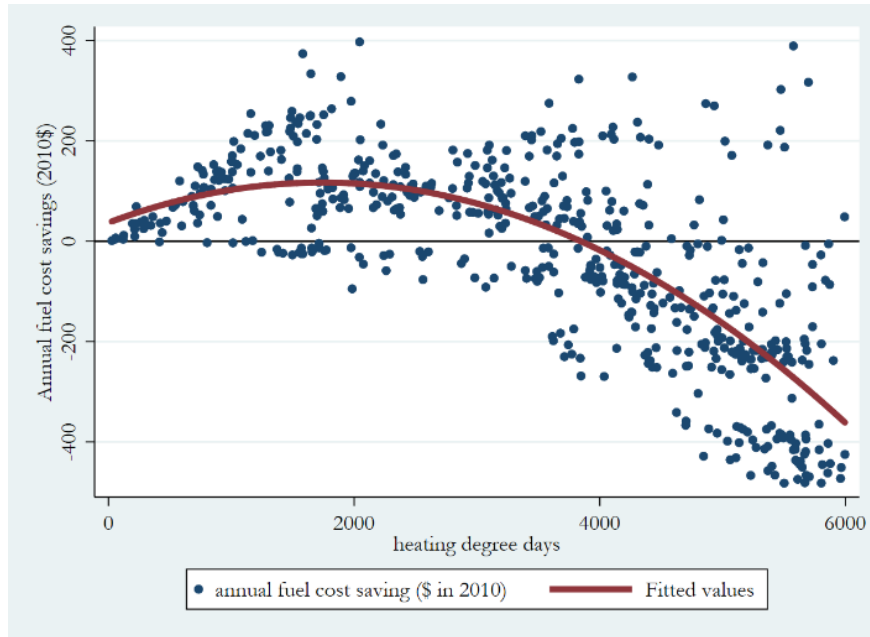
(2) The relationship between the price premium and climate (heating degree days and cooling degree days)

My results suggest the price premium higher in places that have an average number of heating degree days relative to other places. In places with very low heating degree days (HDD) which do

not need much heat, people are unlikely to pay a big upfront premium for efficient heating (e.g., the payback time for a heat pump versus conventional heating systems might be too high, because annual fuel cost savings for a heat pump compared to conventional heating systems is small in places with very low heating degree days). (See **Supplementary Figure 2**). Thus, there is no significant price premium in places with low heating degree days.

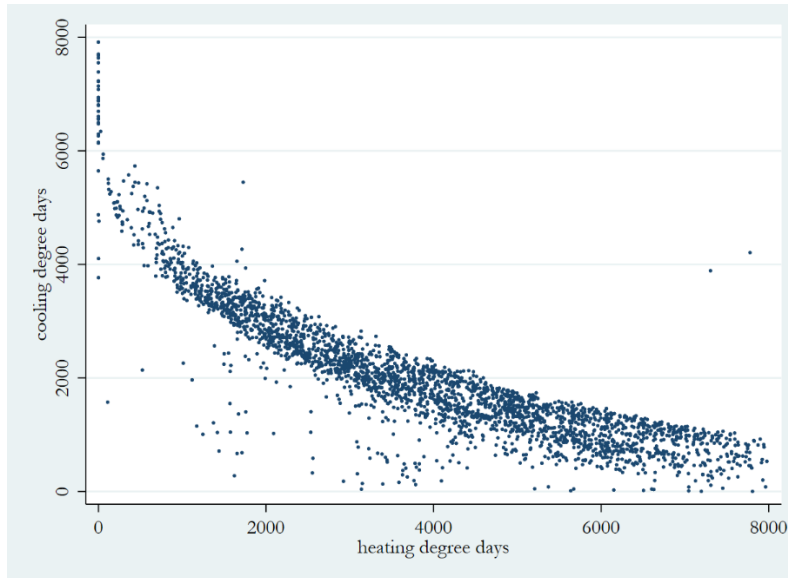
In places with very high heating degree days, heat pumps do not work well at low temperatures. For instance, when it is very cold ($<5^{\circ}\text{F}$), the heat pump turns into a resistive heater and can be very expensive to operate. I find that the fuel cost savings compared to conventional natural gas furnaces are negative in places with high heating degree days (See **Supplementary Figure 2**). Thus, people are not likely to adopt the heat pumps and there is no significant price premium in places with very high heating degree days.

These findings also imply that consumers care about the private benefits of installing a heat pump. Thus, policymakers should provide more information about future savings to encourage heat pump adoption. Also, researchers should spend more effort to improve the efficiency of heat pumps in extremely cold areas.



Supplementary Figure 2. The annual household heating fuel cost savings associated with a switch from conventional heating systems to heat pumps, which is obtained from Vaishnav and Fatimah (2020). The fitted values are the prediction for fuel cost savings from a linear regression of fuel cost savings on HDD and HDD^2 . The data of heating degree days and cooling degree days were obtained from the National Oceanic and Atmospheric Administration. The heating degree days and cooling degree days are computed based on a base temperature of 65 Fahrenheit degrees.

The cooling degree days are highly (negatively) correlated with the heating degree days (See **Supplementary Figure 3**). The relationship between the price premium and the heating degree days explains the relationship between the price premium and the cooling degree days. I can use the relationship between the fuel cost savings of heat pumps and heating degree days to explain the relationship between the price premium and cooling degree days.



Supplementary Figure 3. The correlation between heating degree days and cooling degree days
 Data source: National Oceanic and Atmospheric Administration

(3) The relationship between the price premium and the penetration rate of heat pumps

The insignificant and lower price premium when the penetration rate is small can be explained by uncertainty and observational learning in the adoption of novel technologies. During the very early stage of technology adoption, consumers have little knowledge about how to use the technology, its performance, and future return (Strong, 2019). In this case, consumers tend to observe the behavior of another person who has used the novel product to infer the usefulness of this product (Walden & Browne, 2009; Mulder et al., 2003), and then make the decision to adopt it. Empirical evidence suggests observational learning influences people’s decisions on technology adoption in the laboratory experiment (Song and Walden, 2003) and in real stock markets (Walden and Browne, 2008). Thus, the first user will have much less incentive to adopt the new product (Gillingham & Palmer, 2014), which leads to a lower/insignificant price premium of heat pumps when the penetration rate is very low in my study.

For the downward trend when the penetration rate is larger than 0.08 (number of heat pumps per person), the lower house price premium could be due to lower installation costs, information searching costs, and transaction costs, as explained below.

First, the installation costs of heat pumps will decrease with the increase in penetration rate because of the “learning by doing” process (Van Benthem et al., 2008; Bollinger and Gillingham, 2019). The installation workers will be more experienced, and the logistics and warehousing costs will be lower (e.g., it would be more difficult for heat pump adoption if there are only limited inventory in the warehouse) as the penetration rate increases. Gillingham et al. (2016)’s study on solar photovoltaic (PV) industry finds that increasing installer experience leads to a lower installation price of solar PV.

Second, the information searching costs and transaction costs for heat pumps decrease with the increase in penetration rate. Gillingham et al. (2016) on the solar photovoltaic industry finds that higher installer density leads to lower PV installation price because of “lower information searching cost.” It could be similar in the case of heat pumps. Moreover, inexperienced installation workers may extend installation time, which leads to an increase in transaction costs of house owners.

(4) Robustness check using an alternative method

I also conduct a robustness check using a traditional method based on interaction terms between the treatment variable and a set of dummies for different quartiles of the distribution of other influencing factors. **Supplementary Table 1** shows the estimated results, which are consistent with the partially linear varying coefficient model.

Supplementary Table 1. The heterogeneity of the price premium induced by heat pumps using interaction terms

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome: log (sales price)					Outcome: Absolute price
	By Environmental Awareness (%)	By Heat Pump Density (N/Person)	By Annual HDDs	By Annual CDDs	By Personal Income Per Capita (2018\$)	By Personal Income Per Capita (2018\$)
D*Bin1	-0.1101*** (0.0400)	0.4142*** (0.1436)	-0.0003 (0.0115)	-0.0601 (0.0650)	-0.0452 (0.049)	-1303.99 (7624.419)
D*Bin2	0.2061*** (0.0475)	-0.0009 (0.1620)	0.08*** (0.0301)	0.0341 (0.0374)	0.0858 (0.0553)	354.77 (5846.474)
D*Bin3	0.0812** (0.0329)	-0.0148 (0.1481)	0.1191*** (0.0354)	0.2109*** (0.0661)	0.1895*** (0.066)	30867*** (9079.628)
D*Bin4	0.1087** (0.0483)	0.1247** (0.0525)	0.1593*** (0.0491)	-0.0272 (0.0549)	0.1274*** (0.04)	18338.85*** (5945.2)
D*Bin5	0.0858 (0.0588)	0.1229*** (0.0655)	-0.074 (0.0471)	0.2364** (0.0981)	-0.0706 (0.0449)	-11434.34* (6027.52)
D*Bin6	-0.4036*** (0.1229)	-0.0425 (0.0364)	0.0298 (0.0497)	-0.0145 (0.0369)	0.0948*** (0.0269)	10735.45* (4578.074)
D*Bin7	0.0513 (0.0402)	0.0023 (0.0667)	0.0446 (0.0442)	0.2389*** (0.0464)	0.0379* (0.0202)	3503.414 (3112.689)
D*Bin8	0.01256 (0.0115)	0.1306*** (0.0470)	-0.0064 (0.0661)	0.033 (0.0348)	0.0198 (0.0179)	1795.036 (3467.316)
D*Bin9	0.2394** (0.1181)	0.1035*** (0.0378)	0.1488** (0.0707)	0.01 (0.0112)	0.0178 (0.0197)	7517.487* (4564.479)
D*Bin10	-0.0049 (0.0299)	0.0143 (0.0107)	0.0849 (0.0839)	0.0881 (0.0752)	-0.1649*** (0.053)	-50156.3*** (18223.34)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.0564	0.0558	0.0603	0.0575	0.0569	0.0928
Obs	634,952	634,952	634,952	634,952	634,952	599,244
N of Houses	378,267	378,267	378,267	378,267	378,267	356,411

*Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. I divide the distribution of influencing factors into 10 bins based on 9 quantiles (10%, 20%, ..., 90%). Control variables include federal fund rates, annual population density and personal income per capita at the county level, monthly natural gas price at the state level, and annual electricity price at the state level.

Appendix B. The private benefit, public benefit, and cost of switching to heat pumps

Heat pumps offer an energy-efficient alternative to traditional heating and cooling systems like natural gas furnaces and air conditioners. Heat pumps use electricity to move heat from a cool space to a warm space, making the cool space cooler and the warm space warmer. The benefits of switching to heat pumps consist of two parts: the benefits of space heating and the benefits of space cooling. I use fuel cost saving to represent private benefit and use avoided environmental damage to represent the public benefit.

(1) Annual avoided environmental damage and fuel cost saving for space heating associated with a switch to air-source heat pumps with the current power grid

I use the data estimated by Vaishnav and Fatimah (2020) to compute the annual avoided environmental damage (including CO₂, SO₂, PM, and NO_x) and fuel cost saving for space heating associated with a switch to air-source heat pumps for houses included in my analysis. Vaishnav and Fatimah adopt a spatial environmental benefit and private benefit analysis for residential air-source heat pumps at 883 locations in the U.S. These 883 locations spread evenly throughout the country. I find the closest location for each house in my dataset based on longitude and latitude, and use the estimated fuel cost-saving and environmental benefit of the closest location to represent that of the house.

Vaishnav and Fatimah (2020) assume that there are four types of heating scenarios: main heating by a natural gas furnace, main heating by electric resistance heating, main heating by heat pump with natural gas furnace used for auxiliary heating, and main heating by heat pump with

electric resistance used for auxiliary heating. Nowadays, most households use natural gas or electricity as heating fuel sources in the U.S. They assign each of the 883 locations into two types (electric heating and natural gas heating) based on each location's primary heating fuel source. The avoided environmental damage can be computed by differencing the environmental damage of the current heating pattern and heat-pump pattern. The fuel cost saving can be computed similarly.

Supplementary Table 2 and **Supplementary Table 3** show the average fuel cost saving and avoided environmental damage for space heating associated with a switch to heat pumps at the state level.

Supplementary Table 2. The environmental damage induced by space heating per household with the current power grid by different heating types

<i>State</i>	<i>environmental damage by electric resistance heating (2010\$/year)</i>	<i>environmental damage by natural gas heating (2010\$/year)</i>	<i>environmental damage by the heat pump and auxiliary electric resistance heating (2010\$/year)</i>	<i>environmental damage by the heat pump and auxiliary natural gas furnace (2010\$/year)</i>
AK				
AL	58.53	45.70	68.27	70.25
AR	19.43	92.36	142.00	153.07
AZ	0.00	61.71	75.01	78.37
CA	0.00	51.27	56.40	57.18
CO	0.00	201.58	258.23	294.71
CT	0.00	222.35	249.83	276.83
DE	0.00	145.45	306.46	349.98
FL	26.57	5.05	6.61	6.61
GA	60.62	44.86	66.16	67.91
HI				
IA	0.00	233.19	600.22	775.88
ID	0.00	219.12	272.88	297.59
IL	0.00	203.92	385.42	476.87
IN	0.00	192.51	416.15	511.83
KS	0.00	147.01	266.05	311.32
KY	0.00	124.82	198.14	222.97
LA	105.69	17.06	26.48	26.48
MA	0.00	229.62	260.71	296.00
MD	0.00	116.03	254.82	277.45
ME	0.00	283.30	365.56	456.73
MI	0.00	259.58	596.49	754.05
MN	0.00	301.74	820.99	1187.87
MO	0.00	139.99	229.30	267.45
MS	50.58	46.78	69.06	70.77
MT	0.00	266.98	431.88	565.99
NC	17.91	78.90	117.27	121.87
ND	0.00	300.98	861.62	1308.73
NE	0.00	221.77	495.78	632.73
NH	0.00	293.01	311.49	371.03
NJ	0.00	152.53	310.48	342.88
NM	0.00	91.52	118.93	123.58
NV	0.00	151.13	184.49	197.50
NY	0.00	223.08	267.54	314.15
OH	0.00	207.07	459.84	547.76
OK	0.00	100.74	171.23	187.91
OR	0.00	156.30	178.88	183.65
PA	0.00	205.60	438.89	509.30

<i>RI</i>	0.00	220.86	248.76	271.60
<i>SC</i>	49.17	53.17	81.39	83.70
<i>SD</i>	0.00	269.53	660.03	933.31
<i>TN</i>	0.00	96.46	144.79	154.49
<i>TX</i>	70.05	24.82	34.82	35.10
<i>UT</i>	0.00	179.03	222.32	238.17
<i>VA</i>	0.00	115.16	215.35	239.72
<i>VT</i>	0.00	264.50	335.16	410.45
<i>WA</i>	0.00	170.77	199.73	206.41
<i>WI</i>	0.00	271.95	694.36	933.49
<i>WV</i>	0.00	157.31	356.64	406.25
<i>WY</i>	0.00	233.87	308.42	359.24

Data source: Vaishnav and Fatimah (2020)

Supplementary Table 3. The fuel cost of space heating per household with the current power grid by different heating types

<i>State</i>	<i>Fuel cost of natural gas furnace heating a homeowner has to pay (2010\$/year)</i>	<i>Fuel cost of electric resistance heating a homeowner has to pay (2010\$/year)</i>	<i>Total fuel cost of heat pump and auxiliary natural gas furnace heating a homeowner has to pay (2010\$/year)</i>	<i>Total fuel cost of heat pump and auxiliary electric resistance heating a homeowner has to pay (2010\$/year)</i>
AK	1592.02	0.00	3614.93	5393.49
AL	264.47	147.72	173.85	177.52
AR	425.02	40.71	292.84	309.03
AZ	392.54	0.00	262.93	271.55
CA	248.01	0.00	292.29	296.34
CO	615.93	0.00	876.37	1002.46
CT	1115.36	0.00	1388.83	1541.88
DE	684.29	0.00	600.92	663.70
FL	42.28	72.53	18.01	18.01
GA	268.23	152.44	167.90	171.05
HI	0.68	1.51		
IA	773.22	0.00	1182.93	1487.80
ID	739.67	0.00	797.55	864.75
IL	647.04	0.00	824.59	991.14
IN	616.33	0.00	743.40	884.80
KS	597.29	0.00	666.39	762.90
KY	516.89	0.00	416.26	457.26
LA	79.76	203.08	50.82	50.82
MA	1127.37	0.00	1405.88	1600.13
MD	535.50	0.00	521.14	556.94
ME	1588.92	0.00	1620.93	1974.86
MI	858.66	0.00	1373.26	1694.89
MN	983.72	0.00	1558.85	2154.48
MO	627.64	0.00	583.79	662.43
MS	194.36	109.63	150.69	153.70
MT	805.65	0.00	1108.35	1392.80
NC	365.86	40.25	266.21	274.24
ND	892.56	0.00	1450.71	2089.12
NE	731.52	0.00	945.03	1158.72
NH	1677.72	0.00	1633.15	1930.84
NJ	489.57	0.00	719.61	787.25
NM	306.83	0.00	406.44	422.88
NV	642.98	0.00	597.19	634.35
NY	959.68	0.00	1315.38	1550.41
OH	750.53	0.00	867.18	1001.88
OK	440.19	0.00	333.49	357.65
OR	750.52	0.00	537.84	549.32
PA	838.79	0.00	942.09	1065.48

<i>RI</i>	1206.12	0.00	1207.13	1311.63
<i>SC</i>	275.98	164.15	204.28	208.52
<i>SD</i>	843.82	0.00	1224.93	1648.37
<i>TN</i>	365.21	0.00	306.55	323.37
<i>TX</i>	120.50	165.49	84.28	84.81
<i>UT</i>	678.83	0.00	709.02	755.59
<i>VA</i>	510.49	0.00	455.32	493.19
<i>VT</i>	1519.56	0.00	1634.43	1970.93
<i>WA</i>	751.85	0.00	539.57	553.47
<i>WI</i>	885.07	0.00	1407.08	1834.49
<i>WV</i>	595.68	0.00	619.05	686.87
<i>WY</i>	828.13	0.00	1024.93	1187.24

Data source: Vaishnav and Fatimah (2020)

(2) Annual avoided environmental damage and fuel cost saving for space cooling associated with a switch to air-source heat pumps

I estimate the fuel cost saving of space cooling based on the 2015 Energy Information Administration (EIA) RECS Data, which includes the annual average energy expenditure on space cooling per household in each census division in 2015. I assume that (1) annual energy expenditure for the future years is the same as that in 2015, (2) all the space cooling systems are run by electricity, and (3) air-source heat pumps can reduce the cost of space cooling by 50%. DOE mentions that heat pumps can save as much as 75% on energy for space cooling (<https://www.energy.gov/energysaver/heat-and-cool/heat-pump-systems>). I take a more conservative approach and use 50%. Thus, I use half of the annual average energy expenditure on space cooling to represent the fuel cost saving of spacing cooling associated with a switch to heat pumps.

I estimate the annual avoided environmental damage by using the annual average energy consumption on space cooling per household from 2015 RECS data and the marginal damage

factors of carbon dioxide and pollutants by NERC regions estimated by Holland et al. (2016). The census division of Pacific is located in the Western Electricity Coordinating Council (WECC) region. I used the marginal damage factors for the WECC for the division of the Pacific. The division of South Atlantic is overlapped with three NERC regions, which are the Florida Reliability Coordinating Council (FRCC) region, Reliability First Corporation (RFC) region, and SERC Reliability Corporation (SERC) region. Thus, I use the average of the three NERC regions to represent the division of South Atlantic. Then, I estimate the avoided environmental damage of switching to heat pumps by assuming that heat pumps can reduce the energy consumption of space cooling by 50%.

(3) Lifetime fuel cost saving and avoided environmental damage associated with a switch to heat pumps.

The present value of the lifetime environmental benefits and fuel cost saving associated with a switch to heat pumps are obtained by the following equation

$$S \times \left[\frac{1 - (1 + r)^{-n}}{r} \right]$$

where **S** is the annual fuel cost-saving or environmental benefits of a switch to heat pumps. **n** denotes the number of years that the benefits or savings are assumed to be obtained. I suppose that consumers can accrue over 25 years which is the lifetime of a common new air-source heat pump. The **r** is the private discount rate, and I assume it to be 7% annually. The discount rate should reflect the returns those consumers would accrue from other alternative investments. Thus, following Vaishnav and Fatimah (2020), I assume the geometric average of S&P (a stock market

index) returns for the past ten years to be consumers' discount rate, which is just over 7% per annum.

(4) The estimation of fuel cost-saving and environmental benefits in Pacific and South Atlantic

The total benefit (fuel cost-saving and avoided environmental damage) is the sum of benefit on space heating and benefit on space cooling. I estimate the benefit on space heating of these two census divisions using the average of each house's value. I adjust the value into 2018 dollars by the inflation rate.

(5) The cost of installing an air-source heat pump

In the U.S., the majority of installed heat pumps are air-source heat pumps. The cost of installing an air-source heat pump and a traditional HVAC system depends on the size of the home and type of equipment. The cost of installing an air-source heat pump typically ranges from 4,000 to 12,000 dollars. The cost of installing a traditional HVAC system typically ranges from 3,000 to 7,000 dollars.

Chapter 4: Essay 3 - The Impacts of Special Environmental Events on Short-run Electricity-Saving Behaviors

Abstract

Policymakers and academics are increasingly interested in using “social nudge” to influence behavior, which are typically inexpensive relative to price-based and mandatory approaches. This study provides rigorous empirical evidence of the impacts of three big special environmental events, as a specific form of nudges, on short-run electricity-saving behaviors using high-frequency smart meter data in Shanghai, China, for both residential and commercial consumers. I find that World Environment Day and National Energy Saving Publicity Week caused commercial users to reduce their electricity consumption by 1.35 kWh/hour and 0.6 kWh/hour intra-event, around 17% and 8% reduction compared to average consumption, but the impacts decayed rapidly once the events ended. Earth Hour did not lead to significant energy-saving effects for both residential and commercial users. I further examine detailed activities implemented during these events to understand the heterogeneous impacts using social media and policy documents data.

1. Introduction

Traditional energy policy instruments focus on changing relative prices (Allcott, 2011) or setting mandatory standards as the major force altering energy demand to improve energy efficiency and encourage energy conservation behaviors. These traditional approaches, such as carbon and pollution taxes, energy efficiency subsidies, building codes, and mandatory standards, suffer from expensive legislation and implementation costs (Allcott, 2011); these instruments can

also possibly generate inequitable outcomes (Hahn & Metcalfe, 2021). Academics and policymakers are increasingly interested in another complementary approach – “social nudges”, such as information provision and persuasion – aimed at altering consumer behaviors. Nudges are typically inexpensive compared to price-based approaches and energy efficiency standards. As Bertrand et al. (2010) stated, carefully crafted psychological cues can exert significant effects on consumer demand that are comparable to large changes in relative prices (LaRiviere et al., 2014).

Special environmental events, such as Earth Hour, World Environment Day, and Chinese National Energy Saving Week, can be regarded as a form of “nudge.” These events have been globally popular for decades of history (See detailed introduction in section 2). A large number of governments and NGOs have been spending great efforts on organizing them. For example, in the policy document of *2017 working arrangements for energy conservation, emission reduction and tackling climate change*, the Shanghai Development and Reform Commission required government institutions at various levels to organize publicity campaigns on the day of big environmental events in order to improve citizens’ environmental protection and energy conservation awareness. These events aroused significant public attention in Shanghai evidenced by social media data (See section 2). However, few studies provide rigorous quantitative evidence of the effect of these environmental events on energy-saving behaviors.

In addition, the practice of Earth Hour provides a new dimension for intervention studies aimed at energy conservation and environmental protection. Studies divide the non-pecuniary interventions aimed at encouraging energy conservation into the following typical categories (Abrahamse et al., 2005): mandatory standards, commitment, goal setting, information provision (e.g., workshop, mass media campaign, and energy audits), self-feedback (e.g., energy bill reminder), comparative feedback (e.g., Opower letters)(Allcott, 2011). The event of Earth Hour

adds a new form of intervention, which organizes a unique symbolic action of switching off lights for one hour to arouse people's awareness of energy conservation and nature protection. Turning off lights is a symbolic action and does not change social reality instantly, because the impact of turning off lights for a limited number of users for one hour alone on the whole electricity consumption is negligible. The final goal of symbolism here is to influence societal perceptions by using visual actions in order to obtain a public benefit (Berrone et al., 2009). Few studies examined the symbolic actions in information interventions for energy conservation, and specifically, in big environmental events/campaigns. The symbolic actions have been increasingly widely practiced in the environmental context, such as Earth Hour, "Running to Protect the Environment," and Greta Thunberg's sail to New York on a zero-emissions yacht. Related research on these symbolic environmental actions is lacking.

This study provides empirical evidence of the impacts of three special environmental events on consumers' short-run electricity consumption behaviors using high-frequency (hourly and daily) electricity consumption data in 2017 in Shanghai, China, for both residential and non-residential sectors. My high-frequency data (as opposed to monthly data commonly used in previous energy behavioral research) makes it possible to study the impact of these events. Specifically, I examine three such environmental events that have been very popular in China and around the world: Earth Hour, World Environment Day, and National (China) Energy Saving Publicity Week. Here I examine the following research questions: Do these environmental events/campaigns arouse consumers' short-run energy-saving behaviors? Do these events show differences in their impacts? If so, what are the mechanisms driving these differences?

Although the final goal of organizers of these environmental events is to improve the public's environmental awareness in the long-run, it is difficult to identify the long-run effects of these

events with many confounders. My paper still provides useful insights into the long-run impacts even though I focus on short-run energy conservation. The short-run energy-saving behavior can be an important prerequisite for the long-run improvement of environmental awareness. If I find a larger effect on energy conservation in the short run for one event, it provides crucial suggestive evidence that this event has a greater potential to alter people's long-run environmental awareness.

I make three contributions to the existing literature on “social nudges” aimed at energy conservation and environmental protection. First, very few studies focus on the impacts of special environmental events on consumers' electricity consumption behaviors. Analyzing these special events is important because worldwide there have been increasing efforts led by governments and NGOs to raise energy-saving awareness through these environmental events. Earth Hour and World Environment Day have grown to engage more than 140 countries worldwide annually. It is critical to understand whether such efforts could alter consumer energy-conservation behaviors, even in the short run. Second, I conduct a comparative analysis of different effects between the Earth Hour (symbolic campaign) and other typical information-provision environmental events. Third, most studies on nudges and electricity consumption behaviors have only examined residential consumers (Allcott, 2011; Costa and Kahn, 2013; Allcott and Rogers, 2014; LaRiviere et al., 2014; Ferraro and Price, 2013). My study examines both residential and commercial consumers.

Here I show that World Environment Day and National Energy Saving Week caused commercial users to reduce their electricity consumption by 1.35 kWh/hour and 0.6 kWh/hour within the event, around 17% and 8% reduction compared to average consumption, but the impacts decayed post-event. Earth Hour did not lead to significant electricity-saving behaviors for both commercial and residential users. I further explore the mechanisms behind the different impacts

by investigating the interventions adopted during these events, evidenced by related policy documents and social media tweets located in Shanghai. I find most interventions adopted during World Environment Day and National Energy Saving Week directly provided knowledge and skills about how to implement energy-saving behaviors. Most activities adopted during Earth Hour are symbolic actions (such as turning off lights, running, art performance, etc.). Although the symbolic actions cannot directly teach people how to save energy, they have the advantages of fast spread evidenced by social media. Policymakers should combine the merits of the two types of events/campaigns in future campaign design.

2. Introduction to the three special environmental events

Earth Hour is a worldwide movement first initiated by the World Wildlife Fund (WWF) in 2007, which organizes an inimitable symbolic activity that switches off lights for one hour in order to encourage people to protect the environment and save energy. More than 7,000 cities and towns across 187 countries and territories have followed and organized the activities of Earth Hour since 2007. In 2017, the Earth Hour was held at 8:00 PM on 25th March in Shanghai, China. Many private companies, residential communities, and landmark buildings volunteered to turn off lights for one hour to participate in this event.

World Environment Day was originally established by United Nations in 1974. It has become a global event for encouraging awareness and action on issues from energy saving, human overpopulation, marine pollution, and climate change, to sustainable consumption, with the participation of more than 140 countries annually. It is celebrated on the 5th of June every year.

The Shanghai government has annually organized information-provision activities with the theme of World Environment Day for many years.

The National (China) Energy Saving Publicity Week was established at *the Sixth Meeting on Energy Conservation of the State Council of China* in 1990. Since 1991, the National Energy Saving Publicity Week has been held annually. In view of the nationwide shortage of electricity, the 2004 National Energy Saving Publicity Week was held from November to June. The purpose is to form an intense publicity campaign before the peak of summer electricity consumption, and to arouse people's awareness of energy conservation. In 2017, the National Energy Saving Publicity Week was held from 11th June to 17th June. Shanghai city carried out 440 information-provision activities with the theme of energy conservation and emission reduction during the National Energy Saving Publicity Week in 2017.

These events are a specific form of “nudges” where a substantial amount of information and messages are provided about encouraging energy conservation. These messages are disseminated by relevant government agencies (e.g., Environmental Protection Agency and local district office), non-governmental organizations (NGOs), private companies, and individuals via channels such as social media, news reports, and organizing publicity activities. More importantly, all the events did not include any mandatory orders, such as requiring users to reduce electricity consumption. I further discuss the detailed activities and interventions during these events in section 6 of mechanism analysis.

These environmental events did arouse public attention, evidenced by the tweets of social media. **Figure 4.1** presents the evolution of public attention to these events on social media in Shanghai in 2017. I web-scraped all the tweets including keywords of my interest during the time around the events of users located in Shanghai in 2017 from Sina Weibo, the largest social media

platform in China (See data details in section 3). I find that the number of tweets with the words of the events' names peaked significantly on the day of these events. Simultaneously, the number of tweets with the terms of “energy saving” also peaked during these events. Particularly, Earth Hour aroused much greater public attention in Shanghai than the other two events, which could be due to the inimitable symbolic activity that switches off lights for one hour. This paper aims to investigate further whether these events actually influenced consumers' energy-consumption behavior.

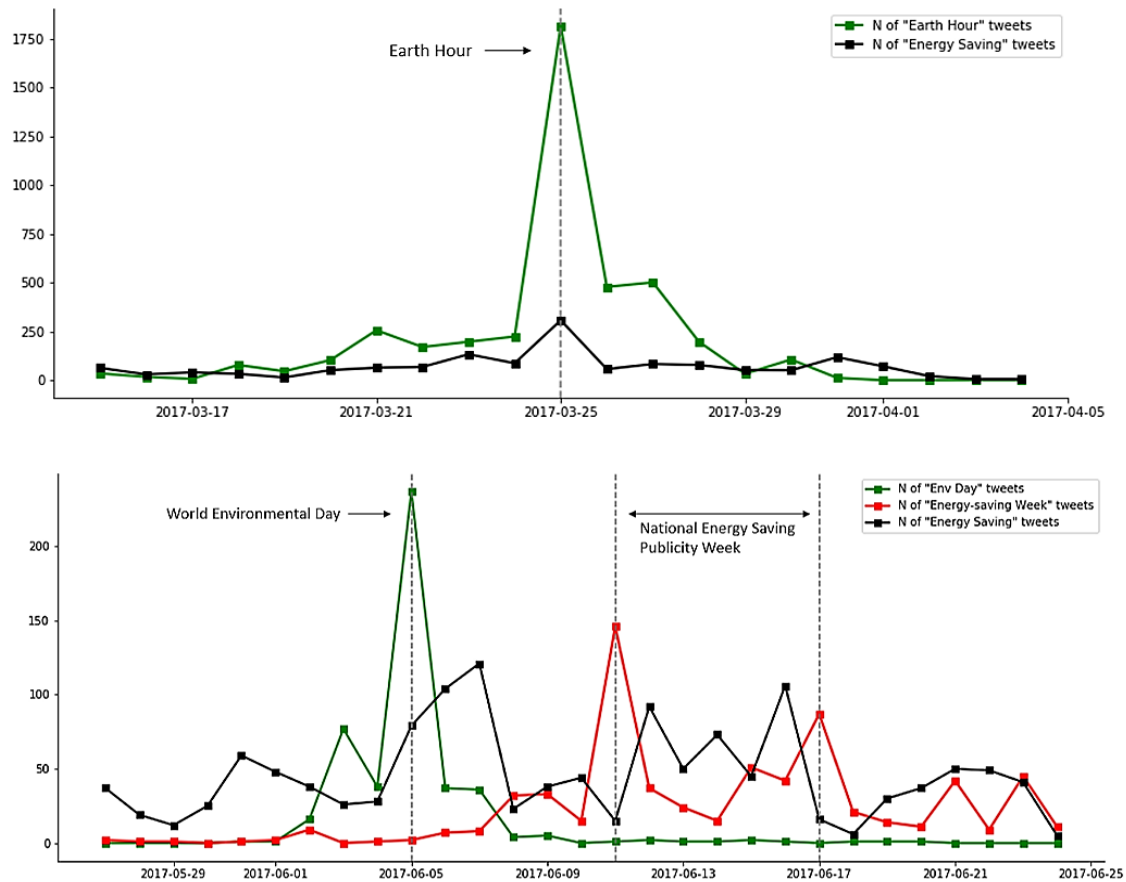


Figure 4.1 The evolution of public attention about these events on social media in Shanghai in 2017.

Note: “Earth Hour” tweet means the tweet including the words of “Earth Hour” in Sina Weibo. “Env Day” tweet means the tweet including the words of “World Environment Day” in Sina Weibo. “Energy-saving Week” tweet means the tweet including the words of “National Energy Saving

Publicity Week” in Sina Weibo. “Energy Saving” tweet means the tweet including the words of “energy saving” in Sina Weibo.

3. Data

3.1 Smart meter high-frequency data

To estimate the impact of the events on electricity consumption, I make use of a smart-meter high-frequency data on individual commercial and residential electricity use. I obtained the individual commercial electricity use data at 15 minutes’ level from The State Grid Corporation (SGC), which is a panel data that covers 684 consumers randomly drawn from all the smart-metered commercial consumers in Pudong, Shanghai over a one-year period from 01/01/2017 to 02/28/2018. In order to merge with the hourly weather data and reduce data noise, I aggregate the 15-minute data to hourly frequency. Based on the definition provided by SGC, commercial users are the users that conduct profitable activities (e.g., shopping malls, office buildings, factories, etc.). I also obtained the individual residential electricity use data at a daily level from SGC covering 1780 consumers randomly drawn from all the smart-metered residential consumers in Pudong, Shanghai, from 01/01/2017 to 02/28/2018. Both the commercial and residential data provide meter ID, consumer type, timestamps of data records, and hourly/daily electricity consumption (kWh). The smart meter data used in my study is anonymous and de-identified.

Table 4.1 shows the descriptive statistics of electricity consumption data of commercial and residential users. For comparison, I aggregate the commercial hourly data to daily frequency and list it in the second row of **Table 4.1**. **Figure 4.2** shows the evolution of average daily electricity consumption for commercial and residential users from 01/01/2017 to 02/28/2018. I further plot the distributions of annual average daily electricity consumption (kWh) for commercial and residential users in my sample (See **Figure 4.3**). I find that residential users’

consumption is more concentrated on small values but also includes more high-consumption users than commercial users.

Table 4.1 The descriptive statistics of electricity consumption data of commercial and residential users.

Variable	Obs	Unit	Mean	Median	Std. Dev.	Min	Max
Hourly Electricity Usage of Commercial users	5,907,352	kWh	7.97	1.65	17.94	0	200
Daily Electricity Usage of Commercial users	247,513	kWh	190.33	63.60	355.87	0	4352
Daily Electricity Usage of Residential users	669,941	kWh	185.88	8.17	389.76	0	2000

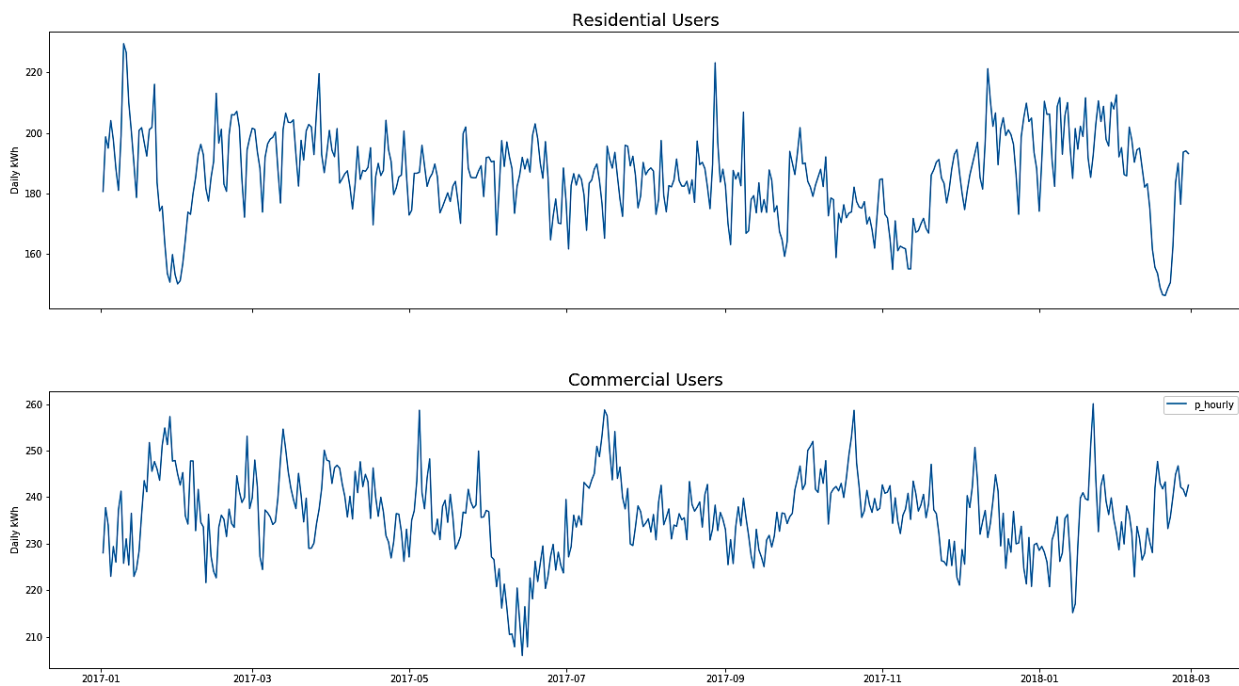


Figure 4.2 The evolution of average daily electricity consumption for commercial and residential users in Shanghai, Pudong, from 01/01/2017 to 02/28/2018.

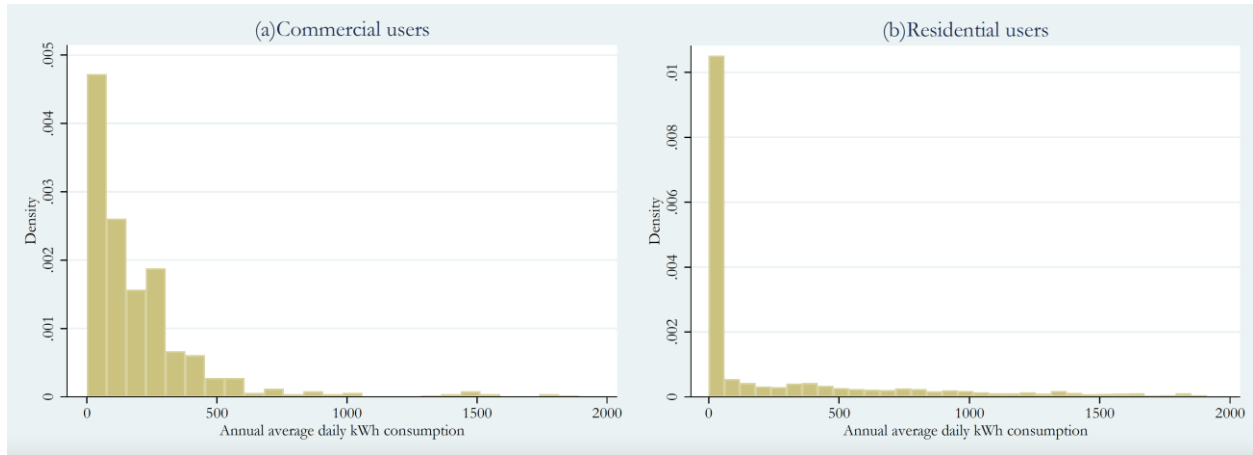


Figure 4.3 The distributions of annual average daily electricity consumption (kWh) for commercial and residential users in my sample.

3.2 Hourly weather data

I obtain the weather data from a local weather station in Pudong, Shanghai, from 01/01/2017 to 02/28/2018 from the National Meteorological Information Center of China. The weather station is the only one located in Pudong, Shanghai. The weather data include timestamps of data records, the highest pressure (hPa), maximum wind speed (m/s), hourly average temperature (°C), relative humidity (%), and hourly precipitation (mm). **Table 4.2** presents the descriptive statistics of the weather data.

Table 4.2 The descriptive statistics of the weather data

Variable	Obs	Unit	Mean	Std. Dev.	Min	Max
Temperature	1,451,932	°C	15.79	9.58	-5.8	39.4
Air pressure	1,452,096	hPa	1017.9	8.87	997.3	1037.5
Relative humidity	1,451,932	%	73.06	19.94	12	100
Maximum wind speed	1,452,096	m/s	1.86	0.98	0	6.0
Hourly precipitation	1,450,725	Mm	0.139	0.88	0	34.2

3.3 Data used for identifying activities during the events

In order to identify activities during the events, I make use of policy documents data and social media data. (1) Policy documents data. I sort out 10 Chinese policy documents related to the special environmental events in Shanghai, which are 2016-2019 *working arrangements for energy conservation, emission reduction and tackling climate change* introduced by Shanghai Development and Reform Commission, 2016-2019 *notice on activities of National Energy Saving Publicity Week and National Low Carbon Day* introduced by National Development and Reform Commission, 2017 and 2019 *activities arrangement of Energy Saving Publicity Week of Shanghai* introduced by Shanghai Economic and Information Commission. (2) Social media data. I web-scraped tweets located in Shanghai published during the time around the event (from 03-15-2017 to 06-26-2017) using four different keywords (“Earth Hour”, “World Environment Day”, “Energy Saving Publicity Week”, and “Energy Saving”) respectively from Sina Weibo, the biggest social media platform in China. **Table 4.3** presents the description of my scraped tweets.

Table 4.3 The description of the web-scraped tweets from Sina Weibo

Keyword	Time range	Location	Number of tweets
Earth Hour	2017.3.15-2017.4.4	Shanghai	7,198
World Environment Day	2017.5.26-2017.6.27	Shanghai	480
Energy Saving Publicity Week	2017.5.26-2017.6.27	Shanghai	743
Energy Saving	2017.3.15-2017.6.27	Shanghai	9,830

4. Methodology: two-step local linear method

I utilize a two-step local linear method in conjunction with high-frequency data as my main approach to estimate the short-run average treatment effect of special environmental events on consumers' electricity consumption.

My approach comes from two-step Regression Discontinuity in Time (RDiT) (Hausman and Rapson, 2018), but is not a Regression Discontinuity (RD). I apply the approach for the following reasons. Because there is no cross-sectional difference in treatment to enable us to conduct a difference-in-differences analysis, I have to estimate and rule out the effect of confounding factors (weather, time periodicity) on electricity consumption. I also need to narrow down the time window of observations to control for unobservable time-variant trends, which makes the estimation of the effect of weather and time (e.g., day of the week, holiday) infeasible in a narrow time window in a single event-study regression. Therefore, I adopt the following two-step approach.

In the first stage of regression, I apply the following econometric model to estimate the impacts of weather, seasonality and time-invariant individual-specific factors on electricity consumption using all the data from 01/01/2017 to 02/28/2018, which helps control confounding factors.

$$\begin{aligned} Power_{it} = & \beta_0 + \sum_{j=1}^6 \beta_{1j} f_j(TEMP_t) + \beta_2 PRS_t + \beta_3 RHU_t + \beta_4 WIN_t + \beta_5 PRE_t \\ & + \sum \pi_k + \gamma_t + \delta_t + \theta_t + \mu_t + \tau_t + \sigma_i + \varepsilon_{it} \quad \dots(1) \end{aligned}$$

where $Power_{it}$ is hourly/daily power consumption (kWh) for consumer i in time t . $TEMP_t$ is hourly temperature. The functions of f_j are spline functions because temperature response varies flexibly. The spline functions can allow slopes within bins smoothing the temperature response, and I obtained five knots both for residential and commercial data after using the spline functions (Li et al., 2018). PRS_t is hourly air pressure. RHU_t is hourly relative humidity. WIN_t is hourly maximum wind speed. PRE_t is hourly precipitation. π_k is a series of fixed effects for all the national legal holidays. γ_t , δ_t , θ_t , μ_t , and τ_t are respectively year fixed effects, month of year fixed effects, day of month fixed effects, day of week fixed effects, and hour of day fixed effects (only used for commercial hourly data), which control for the impacts of time-variant factors on electricity consumption behavior. σ_i is individual fixed effects, which capture all the time-invariant individual consumer-specific characteristics. ε_{it} is an error term. See the first stage estimation results in **Table 4.4**.

Table 4.4 First stage estimation results

	(1) Commercial	(2) Residential
temperature	0.026* (0.015)	1.579 (4.323)
temperature max	-0.015 (0.012)	-5.11* (2.62)
temperature min	-0.095*** (0.012)	0.44 (2.35)
temperature spline1	0.328*** (0.032)	2.742 (2.16)
temperature spline2	-1.45*** (0.098)	2.153 (5.2)
temperature spline3	2.74*** (0.11)	-2.278 (6.09)
air pressure	-0.006*** (0.002)	0.181* (0.033)
relative humidity	-0.007*** (0.0004)	0.019 (0.032)
maximum wind speed	0.023*** (0.007)	2.586*** (0.545)
precipitation	-2.24e-07 (2.09e-07)	-3.333*** (0.824)
Year FE	Yes	Yes
Month-of-year FE	Yes	Yes
Day-of-month FE	Yes	Yes
Day-of-week FE	Yes	Yes
Hour-of-day FE	Yes	No
Holidays FE	Yes	Yes
Individual FE	Yes	Yes
Obs	5,907,352	669,941
R-square	0.0245	0.0005

*Note: Standard errors are clustered at individual level, which are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In the second stage, I save the residuals from the above model, and then a local linear specification is applied using the residuals which are within a narrow bandwidth. I apply a pre-post event-study regression in my second stage instead of using RD to estimate the single gap in the cutoff because of the ambiguous cutoff of receiving the treatment¹⁹ in the case of my study. In addition, since I have a high-frequency hourly/daily dataset, I could limit the time window into a narrow bandwidth (4 days in the pre-treated period and 1 day in the post-treated period) with enough observations to relieve shocks of unobservable confounding factors. I use the observations of 4 days before the events as baseline control group, and I use the observations on each day since the start of events until the fourth day after the event as a treated group respectively, to estimate the treatment effect each day since the event. For National Energy Saving Publicity Week, I use observations four days before 06-05-2017 (World Environment Day) as the baseline control group, because observations four days before 06-11-2017 (Energy Saving Week) could be influenced by World Environment Day. My bandwidth is much smaller compared to existing studies that generally choose 30 days (Anderson, 2014; Bento et al., 2014; Hausman and Rapson, 2018). I run the following local linear specification.

$$Residuals_{it} = \beta_0 + \beta_1 D_t + \varepsilon_{it} \quad \dots(2)$$

where $Residuals_{it}$ is the residuals in the first stage regression model, which is power consumption (hourly consumption for commercial users and daily consumption for residential users) excluding the effects of weather, seasonality, time-invariant consumer specific factors. ε_{it} is an error term. D_t is a treatment variable that takes value one after the event and takes value zero otherwise. In

¹⁹ Although the events start at a specific point in time, different consumers may receive the information of the events at different times.

order to obtain consistent estimates of standard errors, I implemented a bootstrap procedure in the second stage to allow the variance of the first stage to be reflected. Moreover, I cluster standard errors at the individual level to allow arbitrary correlations within individual users.

To further eliminate the concern of contemporaneous confounding factors around the same time with special environmental events, I check all the big events around the time of the three events. I find no other big events around the same time that may systematically influence consumers' electricity consumption. I do not control the electricity price change, because there is no electricity price variation during the time window I investigate.

5. Results

5.1 The average effect of special environmental events on electricity consumption

I aim to investigate whether these environmental events/campaigns arouse consumers' short-run energy-saving behaviors and compare the different effects of these events. **Figure 4.4** plots the average treatment effect of the special environmental events on electricity consumption each day. Commercial users had significant energy-saving behaviors within the National Energy Saving Publicity Week, but the energy-saving effect decayed rapidly to be insignificant when the week ended. Commercial users also had significant energy-saving behaviors on the day of and on the second day after the World Environment Day, but the energy-saving effect decayed rapidly over the next two days. For residential users, World Environment Day and National Energy Saving Publicity Week exert no statistically significant effects on electricity-using behaviors.

Earth Hour had no significant impact on commercial users' electricity consumption. At the same time, residential users increased electricity consumption on average significantly on the first

and second days after Earth Hour. This average increase could be due to the increased consumption of some very-high-consumption residential users who had a higher intertemporal consumption variance and were not influenced by Earth Hour²⁰.

To conclude, commercial users saved electricity consumption statistically significantly by 1.35 kWh/hour and 0.6 kWh/hour on average within World Environment Day and National Energy Saving Publicity Week, around 17% and 8% reduction compared to average consumption. However, Earth Hour did not lead to significant average energy-saving effects for both residential and commercial users. All the statistical estimation results can be found in **Appendix A**.

²⁰ I find that residential users' consumption is more concentrated on small values but also includes much more high-consumption users than commercial users, by comparing the distributions of annual average daily electricity consumption (kWh) of commercial and residential users (See **Figure 4.3**). The increased residential average electricity consumption after Earth Hour might be due to the increased consumption of some high-consumption users who had higher intertemporal consumption variance. The average increased usage after Earth Hour only accounts for 2.3% of the average usage of high-consumption users (top 5%).

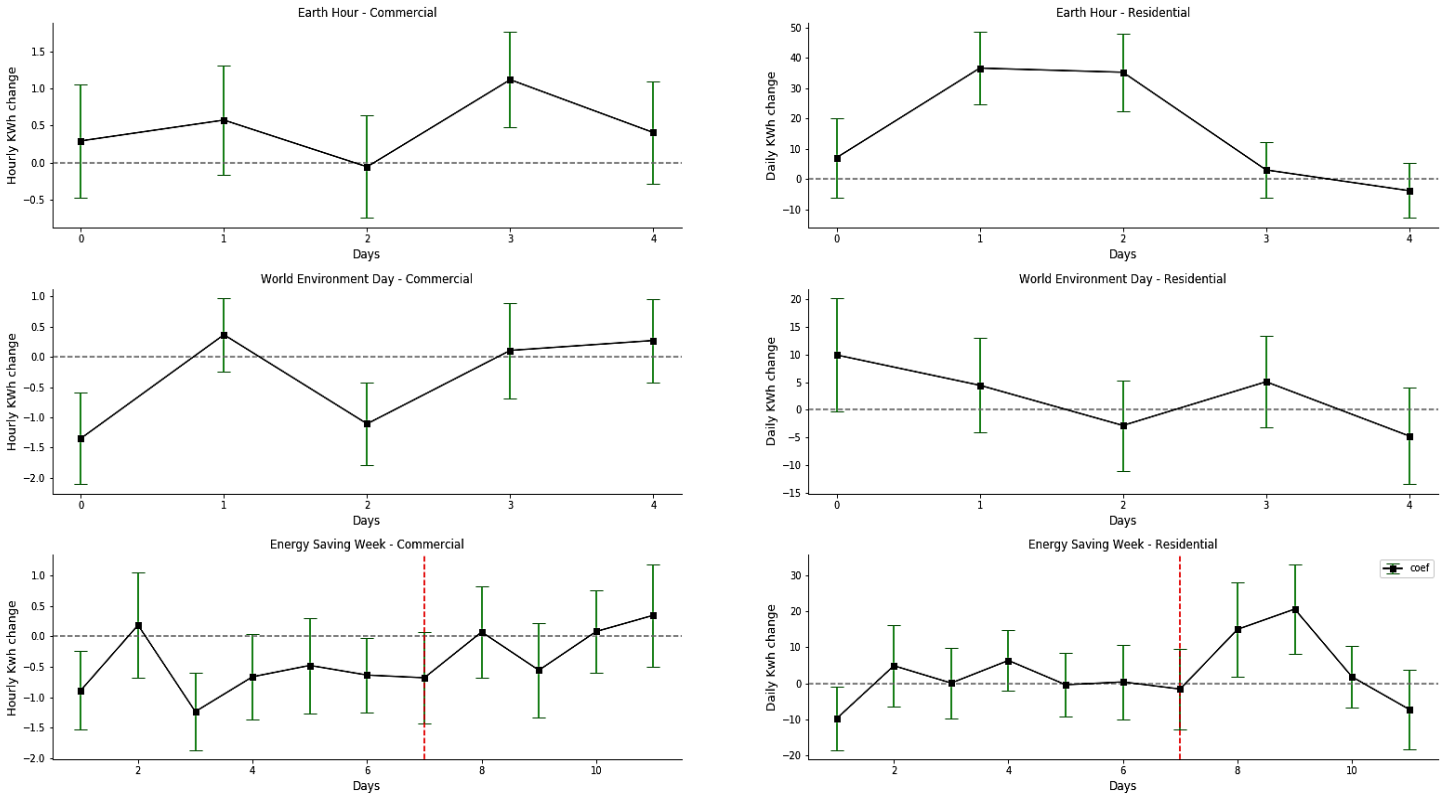


Figure 4.4 The average treatment effect of the special environmental events on electricity consumption each day from the start of the event until the fourth day after the event.

Note: The x-axis is the number of days. For Earth Hour and World Environment Day, day 0 means the day of the event. For National Energy Saving Publicity Week, day 1 to day 7 mean the days within the event. Y-axis is the amount of treatment effect (electricity consumption change on hourly/daily average) of the event on power consumption each day. I use the observations four days before the event as a baseline control group. The green bar is the 90% confidence interval.

I run sensitivity checks by changing the second-stage time window to a different number of days (3 days and 5 days) in the pre-event periods in my two-step local linear method. The results are consistent with my main results (See **Appendix B**). In addition, I develop an alternative machine learning approach to compute the treatment effects as a robustness check. The results are also consistent with my main findings (See **Appendix C**).

5.2 The intraday hourly treatment effects

High-frequency data allows us to investigate the intraday hourly heterogeneity of treatment effects. Here I only investigate the hourly heterogeneity for the commercial users on the day/week of the events for two reasons. First, the energy-saving behaviors were most likely to happen during the events based on above findings. Second, daily residential data cannot allow us to run the hourly estimation. To examine the hourly heterogeneity, I use the same first-stage regression model and the following model in the second stage for commercial users:

$$Residuals_{it} = \beta_0 + \sum_{H=1}^{24} \beta_H I_H \cdot D_t + \varepsilon_{it} \quad \dots(3)$$

where i indicates individual commercial customers. H indicates the hour of the day. I_H is an indicator dummy variable for each hour of the day. D_t takes value one in the post-treatment period, and takes value zero in the pre-treated period. The key coefficients of interest are the series of β_H which measures the change in hourly power consumption kWh of commercial users caused by special environmental events.

Figure 4.5 presents the intraday hourly treatment effects on commercial users. I find that all the significant electricity-saving behaviors under the events' influences happened in the peak time, because meaningful human activities are a significant source of electricity usage change.

Policymakers should pay special attention to the energy-saving measures during the off-peak times, which can also be a source of energy saving. For instance, shopping malls can switch off all unnecessary lighting equipment to save energy during off-peak hours. Policymakers should pay more attention to encourage energy-saving behaviors during some easily overlooked time windows.

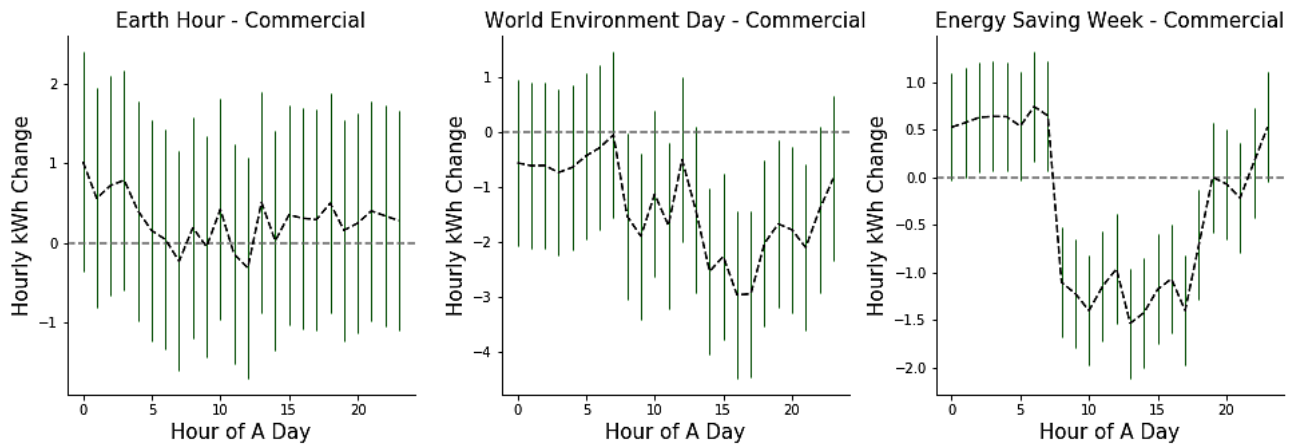


Figure 4.5 The intra-day treatment effects (electricity savings, hourly kWh change) by hour-of-day on commercial users.

Note: The black line represents the coefficients of interaction terms of treatment dummy variable and dummy variables indicating the hour of the day. The green line is the 90% confidence interval.

6. A mechanism analysis

The above findings suggest two opposite effects. World Environment Day and National Energy Saving Publicity Week caused commercial consumers to decrease electricity use significantly on average. In contrast, Earth Hour led to a significant increase in electricity use on average for residential users post-event and had no significant effect on commercial users. To explain the different effects, I conduct a mechanism analysis by investigating what measures were actually implemented during these events.

I reviewed all the related policy documents and web-scraped tweets in 2017 from Sina Weibo (the largest social media platform in China). Policy documents include the requirements and arrangements for certain activities in China. Subordinate government departments and state-owned

enterprises organize the activities following the policy documents. Social media users (including both individual and institutional users) voluntarily publish the activities that they have done.

World Environment Day and National Energy Saving Publicity Week in China are government-lead events while Earth Hour is a voluntary event. In the policy document of *2017 working arrangements for energy conservation, emission reduction and tackling climate change* introduced by Shanghai Development and Reform Commission, World Environment Day and National Energy Saving Publicity Week were listed as two key events aiming to improve the public's environmental awareness. However, Earth Hour did not appear in any government policy documents.

For Earth Hour, I only use social media data. I web-scraped 7,198 tweets including the words of "Earth Hour" published by users located in Shanghai during the time around the event (from 03-15-2017 to 04-04-2017). I summarize all the activities conducted during the event of "Earth Hour" based on social media texts (See **Table 4.5**). For World Environment Day and National Energy Saving Publicity Week, Shanghai city government organized these two events together because the dates of the two events are close, according to the policy document *activities arrangement for 2017 Energy Saving Publicity Week of Shanghai* (introduced by Shanghai Economic and Information Commission). Thus, I treat these two events as one analysis unit and use the data from both policy documents and social media texts. I sorted out ten related policy documents, and web-scraped 1,223 tweets including the words of "World Environment Day" and "Energy Saving Publicity Week" published by users located in Shanghai during the time around the event (from 05-27-2017 to 06-26-2017). I summarize all the activities related to the World Environment Day and National Energy Saving Publicity Week (See **Table 4.5**). The details of policy documents and social media data are in section 3. To conclude, I find most activities during

the World Environment Day and National Energy Saving Publicity Week are directly related to the knowledge and skills of environmental protection and energy saving, while most activities during the Earth Hour are only symbolic behaviors (like turning off lights). My analysis provides suggestive evidence that activities providing knowledge and skills may promote more energy-saving behaviors compared to symbolic activities. Future studies could utilize experimental approaches to provide more rigorous evidence on the comparative effects of the symbolic information and the knowledge-based information.

Table 4.5 The activities conducted during the events in 2017, Shanghai.

2017 Earth Hour	2017 World Environmental Day & National Energy Saving Week
Voluntary Symbolic Campaigns: Turning off lights Night running Cycling Composition contest Art performance Celebrity endorsements on social media	Government-lead Knowledge-based Campaigns: Expert speech Workshop Environmental knowledge competition Distribution of brochures and advertisements Soliciting opinions on energy saving Technology Innovation Competition Environmental policy information session Exhibition Displaying energy-saving cases & products Celebrity endorsements on social media

Data sources: 10 related policy documents, web-scribed social media (Sina Weibo) tweets.

One concern of this mechanism analysis is that the duration of the events might influence their effects. Although turning off lights during the event of Earth Hour happened within only one hour, related information about energy saving and turning off lights was spread all over the day based on my social media data. Thus, the duration of treatment in Earth Hour is similar to that of World Environment Day. Also, although National Energy Saving Week lasted for seven days,

World Environment Day only lasted for one day but exerted a bigger energy-saving effect. Moreover, I find that Earth Hour aroused much more public attention in total than the other two events, according to social media data. Therefore, I cannot attribute the diverse effects to the events' duration.

7. Discussion and policy implications

Worldwide, governments and environmental communities have paid increasing attention and efforts to using the environmental events as a way of nudging consumers to save energy. Given the pressing challenge of climate change, policymakers need to evaluate the effectiveness of various types of instruments (e.g., taxes, standards, or nudges) on reducing energy use and associated carbon and environmental emissions. No prior research has analyzed the effects of special environmental events. I provide the first empirical analysis of the treatment effects of three special environmental events on short-run electricity consumption behaviors for both residential and non-residential consumers. More importantly, I summarize all the activities (including symbolic activities and knowledge-based activities) conducted during these events in the mechanism analysis. It provides practical implications for social-nudge activity organizers in the future. I use data from Shanghai China but my findings can be extended to other cities in the Yangtze River Delta of China because of the similarity in climate, economy, and political institutions. My estimations also have implications for other cities in other emerging markets in which the estimates are hard to conduct. Since a large amount of CO₂ emissions in China comes from heavy industry, future studies on policies to induce behavioral change can be broadened to

include heavy industry regions (e.g., northeastern provinces of China) and also investigate the heterogeneous effects across different industrial and commercial sectors.

Here, I find two major results. On the one hand, commercial users saved electricity consumption statistically significantly by 1.35 kWh/hour and 0.6 kWh/hour on average during the events of World Environment Day and National Energy Saving Publicity Week, around 17% and 8% reduction compared to average consumption. On the other hand, Earth Hour did not lead to any significant energy-saving effects on average for both commercial and residential users.

Moreover, although the World Environment Day and National Energy Saving Publicity Week led to a short-run average energy-saving effect, the effect decayed rapidly once these two events ended.

This study has several implications for policymakers and environmental communities. First, policymakers should combine the merits of the symbolic campaigns and knowledge-based campaigns when they aim to organize large-scale environmental campaigns to arouse people's awareness and behavior of energy conservation and environmental protection. The symbolic campaigns show advantages in faster and wider information dissemination. For instance, Earth Hour arouses much greater public attention on social media than the other two events by organizing a unique and impressive symbolic action – switching off lights for one hour. The knowledge-based campaigns show more advantages in promoting behavioral change. Policymakers should combine the merits of the two types of campaigns. For instance, the organizers of Earth Hour should adopt more activities that directly distribute procedure knowledge about environmental protection and energy saving in the future, in addition to its symbolic action of switching off lights.

Second, policymakers and environmental communities should pay more attention to residential users. I find that commercial users are more likely to respond to the events, while there

are no significant energy-saving effects on residential users. More policy mechanisms as well as targeted strategies (such as providing energy saving tips for residential users, informing residents of their and their neighbors' energy consumptions, and others) should be adopted to facilitate energy-saving behaviors of residential users when organizing the environmental events.

Third, my study contributes to the literature on “demand side management” (DSM) (Zhang et al., 2011; Esther & Kumar, 2016; Barbato & Capone, 2014). Policymakers are increasingly interested in utilizing the DSM to balance energy demand. Special environmental events can be used to increase the willingness of consumers to accept smart appliances to apply the DSM more effectively. Also, I find the electricity demand during the off-peak period should be paid more attention to. There are no significant electricity savings during midnight and early morning. Policymakers should pay more attention to the off-peak period, which could also be a source of energy saving. For instance, shopping malls and office buildings can turn off all the unnecessary lights to save energy during midnight.

Policymakers and environmental communities should continue to support the special environmental events. Although the short-run energy-saving effect caused by the events decayed post-event, we should acknowledge that the short-run behavior change reflects a change in people's awareness. Only the change in awareness can determine people's long-run behavior. Also, “social nudge” is a good supplement to the established price-based and mandatory policies. The Chinese government is planning to reduce subsidies on residential electricity consumption (Reuters, 2021). Public campaigns can be used as a complement to such a price reform and to help alter residential consumers' energy demand. Public campaigns can also help promote the legislation of other “green” policies, such as carbon and pollution taxes, which are politically difficult to implement. The government and environmental communities should continue

organizing special environmental events to improve people's energy conservation and environmental protection awareness.

Appendix

Appendix A. The average treatment effect of special environmental events on electricity consumption

Supplementary Table 1 presents all the daily treatment effects caused by the National Energy Saving Publicity Week. The coefficients of treatment variable measure the treatment effect, or in other words, consumers' change in electricity (kWh) on hourly/daily average after the influence of the events controlling for the confounding factors of weather, seasonality, and time-invariant consumer-specific factors. Standard errors are obtained by a bootstrap procedure and are clustered at the individual level. Day 1 means the first day of the week, day 7 means the last day of the week, day 8 means the first day after the week, and day 11 means the fourth day after the week.

Supplementary Table 2 presents all the daily treatment effects caused by the Earth Hour and the World Environment Day. The coefficients of treatment variable measure the treatment effect, or in other words, consumers' change in electricity (kWh) on hourly/daily average after the influence of the events controlling for the confounding factors of weather, seasonality, and time-invariant consumer-specific factors. Standard errors are obtained by a bootstrap procedure and are clustered at the individual level. Day 0 means the day of the event, day 1 means the first day after the event, day 4 means the fourth day after the event.

I also calculate the average treatment effect within the Energy Saving Publicity Week. I use the observations of seven days within the event as a treated group, and **Supplementary Table 3** presents the estimated results.

Supplementary Table 1. The daily average treatment effects of the Energy Saving Week

Type	Event	Coef.	StdErr	P_Value	Obs	Day
commercial	Energy Saving Week	-0.8873061	0.390787	0.023	65,702	1
commercial	Energy Saving Week	0.1831917	0.5285	0.729	65,698	2
commercial	Energy Saving Week	-1.234467	0.384156	0.001	65,714	3
commercial	Energy Saving Week	-0.6630916	0.426845	0.12	65,742	4
commercial	Energy Saving Week	-0.4773306	0.475547	0.315	65,827	5
commercial	Energy Saving Week	-0.6354886	0.370606	0.086	66,064	6
commercial	Energy Saving Week	-0.6798988	0.456799	0.137	66,028	7
commercial	Energy Saving Week	0.0706964	0.45693	0.877	66,141	8
commercial	Energy Saving Week	-0.556253	0.471616	0.238	66,082	9
commercial	Energy Saving Week	0.0779607	0.408803	0.849	66,045	10
commercial	Energy Saving Week	0.3443088	0.509415	0.499	66,084	11
residential	Energy Saving Week	-9.81473	5.348632	0.067	7,909	1
residential	Energy Saving Week	4.896253	6.904359	0.478	7,945	2
residential	Energy Saving Week	0.0752327	5.996007	0.99	7,935	3
residential	Energy Saving Week	6.358507	5.085761	0.211	7,938	4
residential	Energy Saving Week	-0.402408	5.388365	0.94	7,928	5
residential	Energy Saving Week	0.3864754	6.274323	0.951	7,929	6
residential	Energy Saving Week	-1.598501	6.814249	0.815	7,907	7
residential	Energy Saving Week	15.01335	7.986738	0.011	7,919	8
residential	Energy Saving Week	20.66428	7.606922	0.007	7,925	9
residential	Energy Saving Week	1.80813	5.239599	0.73	7,926	10
residential	Energy Saving Week	-7.259525	6.702474	0.279	7,913	11

* Standard errors are clustered at the individual level.

Supplementary Table 2. The daily average treatment effects of the Earth Hour, the World Environment Day

Type	Event	Coef.	StdErr	P_Value	Obs	Day
commercial	Earth Hour	0.293	0.46427	0.528	75,134	0
commercial	Earth Hour	0.574	0.444414	0.197	75,118	1
commercial	Earth Hour	-0.056	0.418928	0.894	75,075	2
commercial	Earth Hour	1.117	0.390452	0.004	75,110	3
commercial	Earth Hour	0.405	0.416879	0.331	75,088	4
commercial	World Environment Day	-1.350	0.459776	0.003	65,557	0
commercial	World Environment Day	0.369	0.369334	0.318	68,060	1
commercial	World Environment Day	-1.107	0.411017	0.007	65,738	2
commercial	World Environment Day	0.109	0.479376	0.82	65,795	3
commercial	World Environment Day	0.273	0.420201	0.516	65,805	4
residential	Earth Hour	7.045	7.968497	0.377	7,783	0
residential	Earth Hour	36.575	7.253746	0	7,828	1
residential	Earth Hour	35.214	7.800103	0	7,826	2
residential	Earth Hour	2.981	5.518044	0.589	7,831	3
residential	Earth Hour	-3.868	5.481434	0.48	7,829	4
residential	World Environment Day	9.899	6.249725	0.113	7,949	0
residential	World Environment Day	4.427	5.209712	0.396	7,935	1
residential	World Environment Day	-2.836	4.964722	0.568	7,925	2
residential	World Environment Day	5.062	4.993851	0.311	7,930	3
residential	World Environment Day	-4.740	5.279331	0.369	7,919	4

* Standard errors are clustered at the individual level.

Supplementary Table 3. The average treatment effect within the Energy Saving Publicity Week

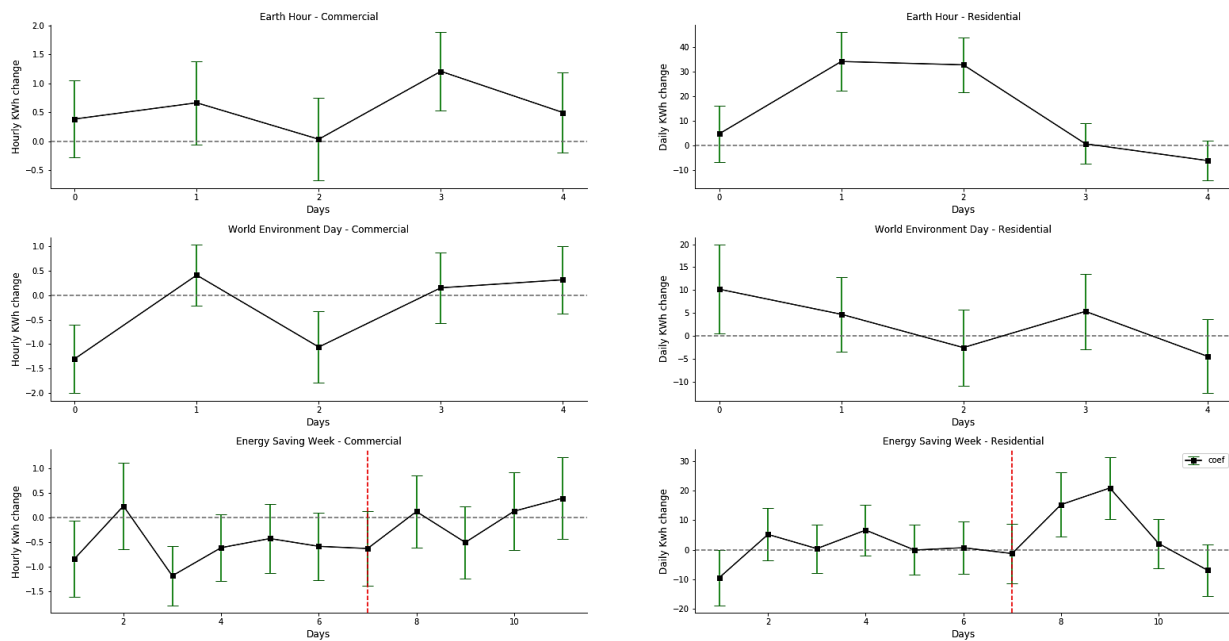
Type	Event	Coef.	StdErr	P_Value	Obs
Commercial	Energy Saving Week	-.627909	.25877	0.016	145,307
Residential	Energy Saving Week	.0186377	4.28219	0.997	17,535

* Standard errors are clustered at the individual level.

Appendix B. Robustness Check I – Changing Time Window

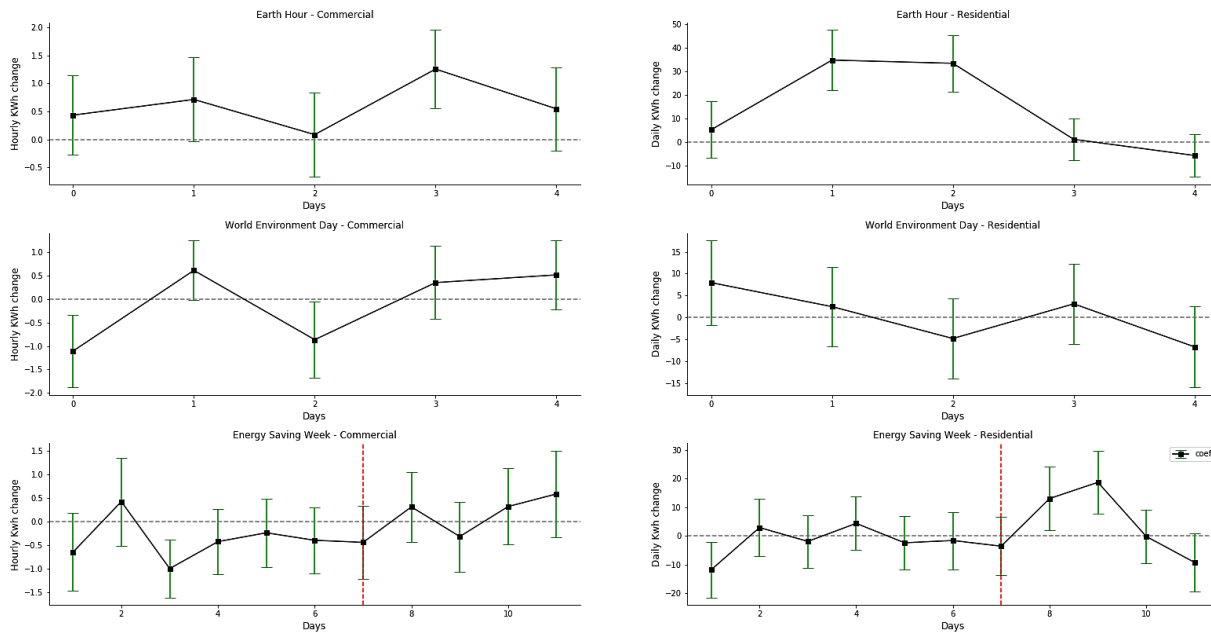
I do robustness checks by changing the time window in my two-stage local linear method.

I first change the time window to 5 days in the pre-treated period and follow the same method to estimate the daily treatment effects of the events. **Supplementary Figure 1** shows the estimated daily treatment effects using observations 5 days before the event as the baseline control group. I find that all the results in **Supplementary Figure 1** are consistent with my main results.



Supplementary Figure 1. The average treatment effect of the special environmental events on electricity consumption on each day from the start of the event until the fourth day after the event. The x-axis is the number of days. For Earth Hour and World Environment Day, day 0 means the day of the event. For National Energy Saving Publicity Week, day 1 to day 7 means the days within the event. Y-axis is the amount of treatment effect (electricity consumption change on hourly/daily average) of the event on power consumption each day. **I use the observations five days before the event as a baseline control group.** The green error bar is the 90% confidence interval.

Secondly, I change the time window to 3 days in the pre-treated period and follow the same method to estimate the daily treatment effects of the events. **Supplementary Figure 2** shows the estimated daily treatment effects using observations 3 days before the event as the baseline control group. I find that all the results in **Supplementary Figure 2** are consistent with our main results.



Supplementary Figure 2. The average treatment effect of the special environmental events on electricity consumption on each day from the start of the event until the fourth day after the event. The x-axis is the number of days. For Earth Hour and World Environment Day, day 0 means the day of the event. For National Energy Saving Publicity Week, day 1 to day 7 means the days within the event. Y-axis is the amount of treatment effect (electricity consumption change on hourly/daily average) of the event on power consumption each day. **I use the observations three days before the event as a baseline control group.** The green error bar is the 90% confidence interval.

Appendix C. Robustness Check II – Alternative Machine Learning Approach

I applied an alternative machine learning approach to estimate the average treatment effect of the special environmental events on commercial users' electricity consumption as another robustness check.

Machine learning algorithms perform much better compared to traditional linear regression in terms of prediction accuracy. I use observations that exclude the information about the events to train the machine learning model, and then use the fitted model to predict “counterfactual” electricity consumption during the time of the events if these events had not happened. I only predict the “counterfactual” hourly electricity consumption for commercial users, which have enough observations to allow us to train the machine learning models. However, although I can provide bounds on my predictions, it is impossible for us to derive standard error for my predictions given that there is no randomization of control and treated groups in machine learning models (Wager & Athey, 2018). Therefore, I only use the machine learning approach as a robustness check.

Model Selection. There are many different machine learning algorithms, so I need to select the most accurate model in terms of prediction for my dataset. I tried five different machine learning algorithms, which are ridge regression, lasso regression, decision tree, bagging trees, and random forest. I randomly draw 80% of observations from the dataset of commercial users' average hourly electricity consumption as training data and the remaining 20% of data as test data. I train different models using the same training dataset and test the performance of each model by calculating the mean absolute error using the same test data. **Supplementary Table 4** presents the

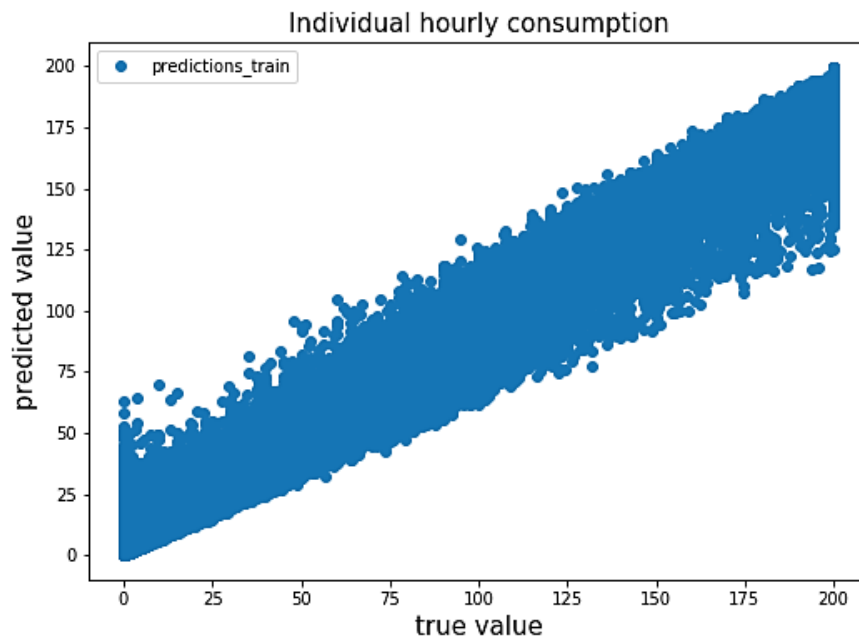
mean absolute errors of different models. The random forest algorithm has the least mean absolute error (0.53 kWh/hour), so I select it as my main machine learning model.

Supplementary Table 4. The mean absolute error of different machine learning models

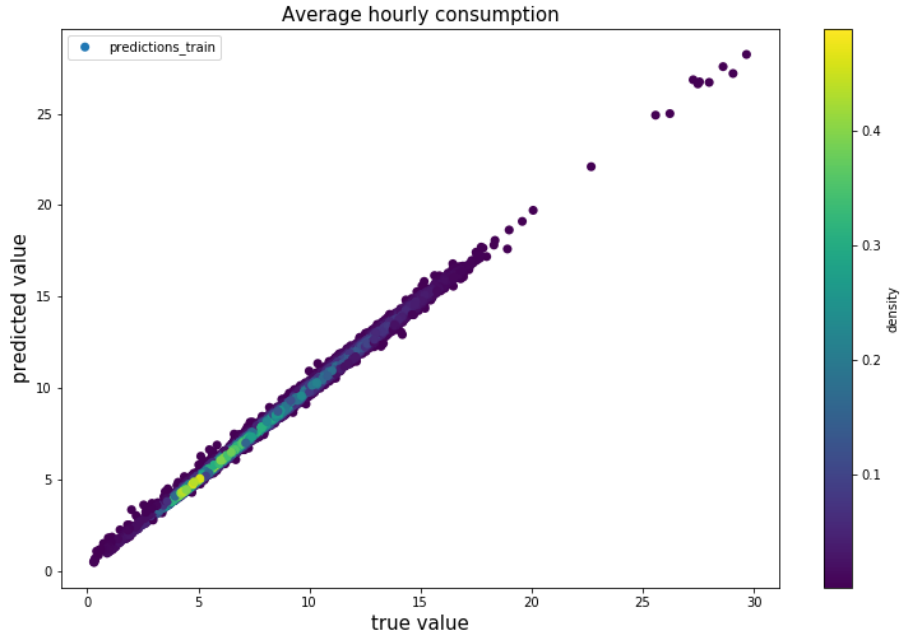
Model	Mean Absolute Error Unit: kWh/hour
Ridge Regression	1.04
Lasso Regression	1.03
Decision Tree	0.94
Bagging Trees	0.88
Random Forest	0.53

Model Validation. I utilize the random forest algorithm to train the model using the data that exclude the information about the event of my interest, and then predict the “counterfactual” electricity consumption during the time of the event. For Earth Hour, I delete the observations from 2017-03-25 to 2017-04-07 from the dataset and then use the remaining data to train the model. Similarly, for the World Environmental Day and National Energy Saving Week, I delete the observations from 2017-06-05 to 2017-06-30 from the dataset and then use the remaining data to train the model. Based on the findings of my previous main approach (the two-stage local liner method), I find the effect of the events decayed rapidly, so I believe the information about the event has been excluded when I train the model. I train the machine learning model for each individual user respectively. The outcome of my model is individual hourly electricity consumption (kWh/hour), while the input variables are same as my main method including the highest pressure (hPa), maximum wind speed (m/s), hourly average temperature (°C), relative humidity (%), hourly precipitation (mm), year, month of year, day of month, day of week, hour of day, holiday, and so on.

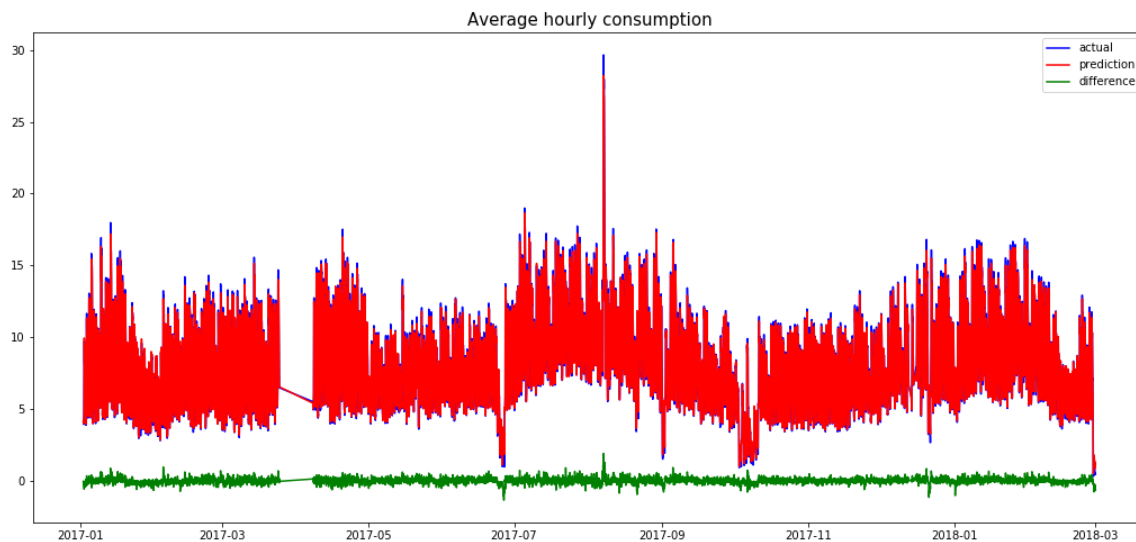
The random forest model performs very well in terms of prediction accuracy. For the Earth Hour, the mean absolute error (MAE) for predicting individual consumption is 0.68, and the Adjusted R^2 is 0.98. I will primarily compare the “counterfactual” predictions with true values at average hourly level (the average of all the users), so I also evaluate the performance of the model at this aggregation level. I find the performance of the model is further improved at the average hourly level. The mean absolute error (MAE) falls to 0.13, and the Adjusted R^2 rises to 0.99. **Supplementary Figures 3, 4, and 5** plot the predicted values versus true values, which indicate the accuracy of the prediction by our machine learning model for the data excluding the Earth Hour.



Supplementary Figure 3. The predicted individual hourly electricity consumption versus the true values by the machine learning model using the data excluding the **Earth Hour**. Values on the 45-degree line mean perfect accuracy.

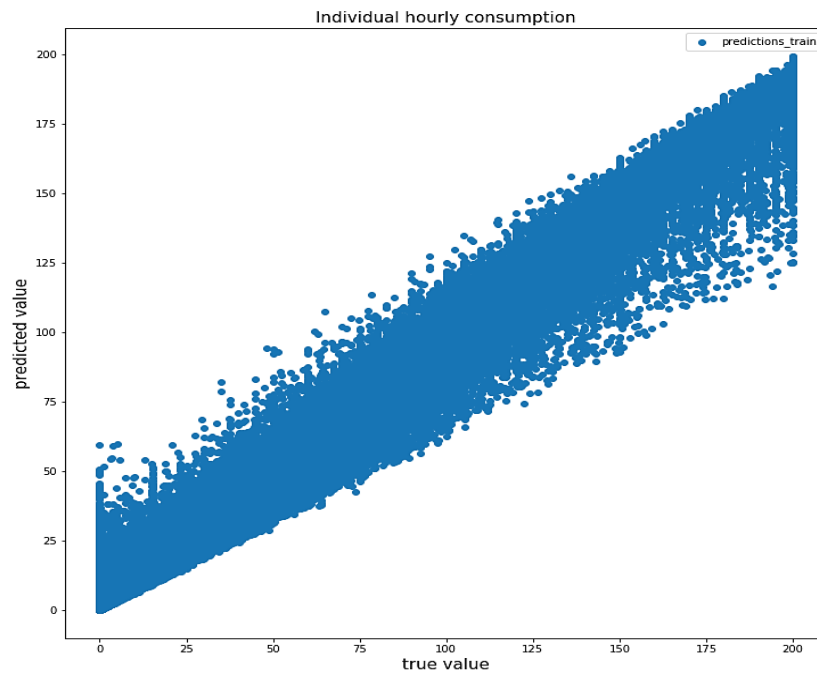


Supplementary Figure 4. The predicted average hourly electricity consumption versus the true values by the machine learning model using data excluding the **Earth Hour**. Values on the 45-degree line mean perfect accuracy.

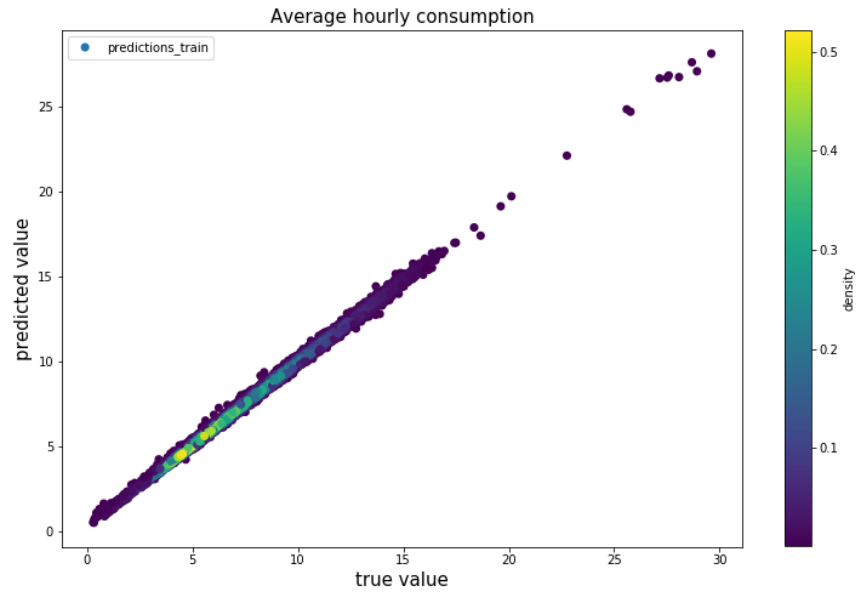


Supplementary Figure 5. The predicted average hourly electricity consumption versus the true values by the machine learning model using data excluding the **Earth Hour**. The red line is predicted values; the blue line is actual values, while the green line is the difference between the predicted values and true values.

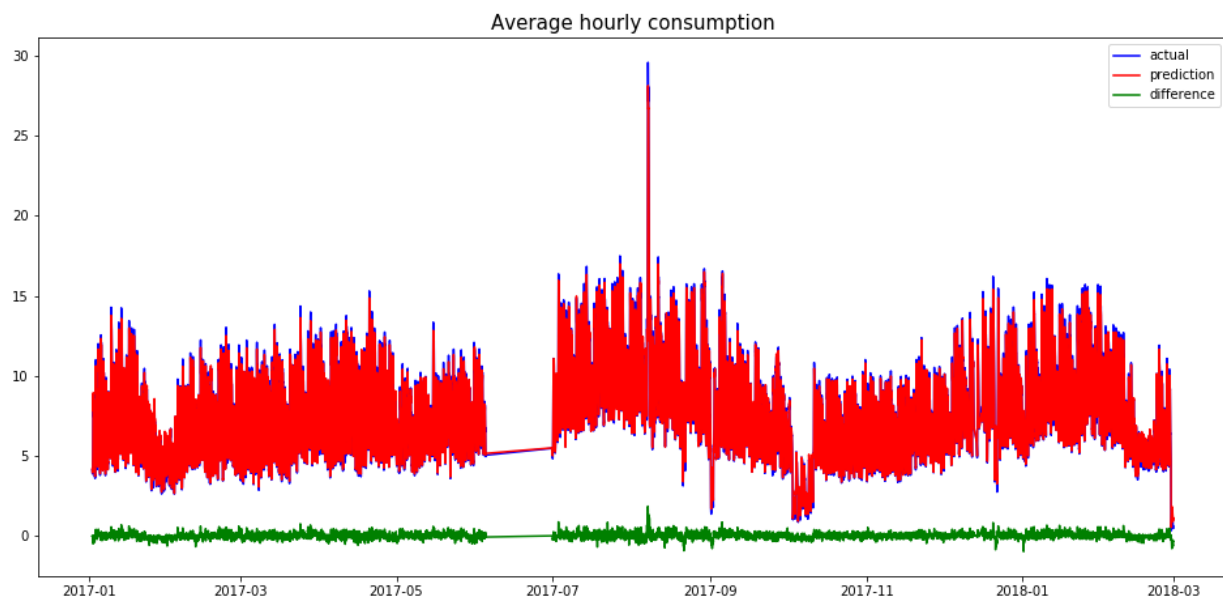
For the World Environmental Day and National Energy Saving Week, my random forest model also performs very well. The mean absolute error (MAE) for predicting individual consumption is 0.66, and the Adjusted R^2 is 0.98. While I evaluate the model at the average level, the mean absolute error (MAE) falls to 0.124, and the Adjusted R^2 rises to 0.99. **Supplementary Figures 6, 7, and 8** plot the predicted values versus true values, which indicate the accuracy of the prediction by my machine learning model for the data excluding the World Environmental Day and National Energy Saving Week.



Supplementary Figure 6. The predicted individual hourly electricity consumption versus the true values by the machine learning model using the data excluding **World Environmental Day and National Energy Saving Week**. Values on the 45-degree line mean perfect accuracy.



Supplementary Figure 7. The predicted average hourly electricity consumption versus the true values by the machine learning model using the data excluding **World Environmental Day and National Energy Saving Week**. Values on the 45-degree line mean perfect accuracy.



Supplementary Figure 8. The predicted average hourly electricity consumption versus the true values by the machine learning model using the data excluding **World Environmental Day and National Energy Saving Week**. The red line is predicted values; the blue line is actual values, while the green line is the difference between the predicted values and true values.

Average Treatment Effect. I utilize my machine learning model to predict the average hourly electricity consumption if the event had not happened as counterfactuals. The difference between the actual average electricity consumption and the predicted counterfactuals is the average treatment effect. **Supplementary Table 5** shows the intra-event and post-event (4 days post-event) average treatment effects. Although my machine learning algorithm still has prediction errors, the magnitude of my model’s mean absolute error is much smaller compared with the treatment effect.

I find that the results of the machine learning approach are consistent with my main approach (two-stage local linear method). World Environment Day and National Energy Saving Week aroused larger electricity savings during the events, but the saving effects decayed post-event. After Earth Hour, the commercial users’ electricity consumption increased significantly post-event.

Supplementary Table 5. Average treatment effects on electricity consumption using machine-learning method

Events	Period	Actual Average Electricity Consumption (kWh/h)	Predicted Average Electricity Consumption (kWh/h)	Average Treatment Effects (kWh/h)	ATE + Mean Absolute Error	ATE - Mean Absolute Error
Earth Hour	intra-event	7.84	8.03	-0.19	-0.06	-0.32
	post-event	8.61	7.89	0.72	0.85	0.59
World Environment Day	intra-event	6.89	7.49	-0.60	-0.48	-0.72
	post-event	7.84	7.97	-0.13	-0.01	-0.25
Energy Saving Week	intra-event	7.39	7.66	-0.27	-0.15	-0.39
	post-event	7.63	7.41	0.22	0.34	0.10

**note: The mean absolute error in this table is obtained by the random forest model using the training data excluding the event of my interest. “Post-event” means four days after the event.*

Chapter 5: Conclusion and Implications

1. Summary of findings

Climate change is becoming widespread, rapid, and intensifying (IPCC, 2021), which could lead to irreversible and serious consequences to society and the natural environment if we do not take action. To address the problem of global warming and climate change, we need to stop or capture emissions from burning fossil fuels. Governments and communities are spending large efforts on constructing more renewable power plants, promoting electrification and energy efficiency to decarbonize end-use applications, and enhancing carbon storage capacity. Many policy tools have been utilized, such as subsidies, tax credits, feed-in-tariff, renewable portfolio standard, building construction code, mandated energy efficiency standard, information-provision campaigns, and many others, to promote the clean energy transition from both sides of demand and supply.

In my dissertation, the three essays are focused on policy tools that promote electrification and energy efficiency in the buildings sector from the demand side. Particularly, I study two types of policy tools, namely the price-based approach and the information-provision approach, which have been widely applied by policymakers and local communities for promoting decarbonization. My dissertation provides the first empirical evidence of the impact of subsidies on heat pump adoption, new private benefits after installing the heat pump in the resale housing market, and the impact of special environment events (a new type of “social nudge”) on consumers’ energy

efficiency behaviors. These three essays provide implications for policymakers on how to better utilize policy tools to facilitate electrification and energy efficiency from three dimensions.

The first essay leverages the geographical discontinuity of incentives by different local utilities in North Carolina to estimate the impact of a rebate program (\$300-400 per system installed) on air source heat pump (a key technology to achieve electrification in space heating) adoption, and I also compare the effect of the rebate with that of two loan programs (with different annual interest rates: 9% and 3.9%). Results show that the rebate program can increase the adoption density by 13% in a year. The rebate is more effective in increasing the heat pump adoption rate compared to the two loan programs under the assumption of comparable demand for replacing heating equipment within the buffer area in my sample. In addition, I also conduct a heterogeneity analysis about the rebate effects by different income groups, which shows that the rebate program is much less effective for lower-income groups compared to higher-income groups. Based on back-of-envelope calculations, I also find that the rebate program can be more cost-effective than the two loan programs.

My second essay still focuses on heat pumps. In addition to direct subsidies (rebate and low-interest loans), providing consumers with information about the private benefits of installing a heat pump can also encourage adopting it. In the second essay, I utilize a nation-wide large dataset on property transaction records and assessed building characteristics (obtained from the Zillow group) to estimate the change in home sales prices after the adoption of air source heat pumps in the U.S. Based on a difference-in-differences model and a lower bound analysis, I find that the heat pump adoption increases the home value by 4%-7% across 23 states of the U.S. Environmentally conscious people, middle class, and residents live in regions with mild climate are more likely to pay a higher price premium for the houses with heat pumps. Particularly, based on my calculations,

I find that the estimated price premium is larger than the installation cost of a typical air source heat pump. This positive message is particularly important in the re-sale market with old buildings, since most new installations of heat pumps are in newly constructed buildings. Policymakers can use the information of positive price premium to encourage the adoption of heat pumps in old buildings in the U.S.

My last essay is focused on the impacts of special environmental events on consumers' energy-saving behaviors based on high-frequency electricity-use data from both residential and commercial users located in Shanghai, China. Particularly, I study three important large-scale events, which are World Environment Day, Earth Hour, and Chinese National Energy Saving Week. Results show that the World Environment Day and National Energy Saving Publicity Week caused commercial users to reduce their electricity consumption by 1.35 kWh/hour and 0.6 kWh/hour intra-event, around 17% and 8% reduction compared to average consumption. Earth Hour did not lead to significant energy-saving effects for both residential and commercial users. I further collect information about the detailed activities implemented during these events to understand the different impacts based on social media and policy documents data. I find that most activities during the World Environment Day and National Energy Saving Week are directly related to the knowledge and skills of environmental protection and energy-saving, while most activities during the Earth Hour are only symbolic behaviors (such as turning off lights, running, and art performances).

2. Study limitations

These three essays have several limitations in terms of data, research design, and representativeness, which are illustrated as following in detail:

In the first essay, one important limitation is the research design of the second and third samples. Because of data limitations, I am not able to obtain observations before the implementation of the two loan programs so I can only estimate the difference in differential trends across the borderline between two utilities, which is not a typical difference-in-differences approach. In the estimation of difference in differential trends, this study is based on an assumption of comparable time-variant demand for replacing heating equipment within the narrow buffer area in my samples. However, I am not able to provide empirical evidence to support this assumption. Interpreting the results from samples 2 and 3 should be cautious. Nevertheless, this study still provides a new framework for future studies to estimate and compare the differential impacts of different incentives for new low-carbon technology adoption. Second, due to the data limitation, I am not able to isolate the impact of loan programs on heat pump adoption, which is an important topic to be studied. While I find that the rebate is less effective for low-income groups, it is worth studying the heterogeneous impacts of loan programs on different income groups. The loan programs could be more effective for low-income groups with credit/liquidity constraints since the upfront cost of new low-carbon technologies (e.g., heat pumps, solar panels, and others) is much higher than typical old technologies. Third, the broader applicability in the first essay is limited. My study is focused on narrow buffer areas between utilities, which could lead to the problem of selection. The characteristics of my samples could be different from residents in other areas. Interpreting the broader applicability of my results should be cautious. Futures studies can conduct

randomized controlled experiments by selecting a representative sample to better enhance the external validity of the study.

In the second essay, there are also several limitations. First, I am not able to observe building attributes before 2016 so I cannot directly control for the time-variant building attributes in the difference-in-differences model to fully rule out the influence of contemporaneous building retrofits on my estimation. Although I utilize a second-best approach - the lower bound analysis, future studies with more data of building attributes over longer time scales can address this issue of omitted variables. Second, although I obtain a nationwide large dataset, there are many missing values in some states (such as New York state) which have a larger number of heat pump installations in reality. My estimations are based on the sample of 23 states, while these states with many missing values cannot be included. Future studies with a more comprehensive dataset can provide analysis across all the states of the U.S. and a detailed heterogeneity analysis by different areas.

In my last essay, the limitations are as follows. First, it is hard to find a comparable control group when studying the impact of big environmental events, since all the areas use the same time in China and I am not able to identify consumers who were influenced by the events and who were not influenced. Without a comparable control group, I use a second-best approach, the two-step local linear method based on high-frequency electricity-use data, to estimate the impacts of these events. Future studies can conduct field experiments to create comparable treated and control groups to better estimate the impacts of public campaigns on human behaviors. Last, my estimations are based on an urban sample in Shanghai, which is the largest city in China. Interpreting the broader applicability of my results should be with caution. Nevertheless, my study

provides a new framework for future studies to explore the impacts of the big environmental events in other areas.

3. Policy implications

My dissertation provides broader implications for policymakers and local communities.

The first and second essays provide important implications for promoting electrification in space heating. Space heating makes a significant contribution to carbon emissions from the buildings sector. More than half of U.S. residents are utilizing fossil fuels (e.g., natural gas, oil, and others) for space heating. Electrifying the space heating with electrical heat pumps plays a more and more important role in deep decarbonization. The U.S. government is planning to provide more funding for subsidies to facilitate building electrification. My study demonstrates that these policies can effectively increase the adoption of heat pumps. Rebate programs could be more effective and cost-effective than loan programs based on evidence of North Carolina under the assumption of comparable demand for replacing heating equipment in my samples. More importantly, I find that the rebate is less effective for lower-income groups. Lower-income groups are less likely to adopt clean energy technology with a high upfront cost. Policymakers need to explore more innovative policies to address the need of low-income people. In addition, based on my second essay, I find a new private benefit, the positive home sales price premium, after the installation of heat pumps, which can reduce consumers' risk when deciding to install the heat pumps. Since the positive price premium is estimated based on a re-sale housing market,

policymakers can introduce targeted information programs for owners of old houses to further facilitate the adoption of heat pumps in old buildings.

Price-based policy tools have been widely applied by policymakers but they have some shortcomings such as expensive implementation costs and unequal outcomes across different groups. Policymakers and researchers are paying more attention to information-provision policy tools. My third essay provides the first empirical evidence of the impact of special environmental events on consumers' energy-saving behaviors. My results imply that the World Environmental Day and National Energy Saving Week led to significant short-run energy-saving effects while Earth Hour did not arouse significant energy-saving effects. It could be due to that most activities that happened in the first two events directly provide the information and knowledge of energy-saving for consumers while the last event did not. However, I also find that the Earth Hour raised much more public attention in social media compared to the other two events, which could be due to the attractive symbolic activities (e.g., switching off lights for one hour). These results provide important implications for policymakers in organizing environmental public campaigns. Campaign organizers should combine the merits of these two types of events to better encourage consumers' behavior changes. On one hand, public campaigns should provide detailed information and knowledge about the benefits and procedures of behavior changes; On the other hand, public campaigns could involve impressive and iconic activities (e.g., switching off lights for one hour) that can be spread fast among the public to further expand the reach of the campaign.

4. Future studies

Future studies can be conducted from several perspectives. First, more studies need to focus on the equity issue in new energy technology adoption (e.g., heat pump, residential solar panel, home battery, and others). The upfront cost of these new technologies is high and vulnerable groups (e.g., social minorities and lower-income groups) are harder to adopt. More studies need to explore the heterogeneity of policy impacts on new technology adoption by different groups of people. Academics and policymakers should consider more innovative policy tools to address the needs of vulnerable groups. Second, more studies need to be conducted in developing countries. The heating and cooling demand in developing countries is projected to be much higher in the coming decades, while fewer studies investigated the issue of energy technology adoption in developing countries compared to those in developed countries. Particularly, the Chinese government has set up an ambitious goal to phase out coal-fired heating in the next ten years in North China. More studies can explore the benefits and costs of heat pump adoption as well as the policy impacts on encouraging heat pump adoption in North China. Third, future studies need to evaluate the long-run effect of public campaigns on people's behavior change. Public campaigns are being used more and more frequently with the aim of influencing people's behavior in the long run, while very few studies provided rigorous estimations on their long-run impacts with empirical evidence. Fourth, to better understand the impacts of public campaigns, future studies could link the campaigns to the theoretical models of psychological and social behavior changes. Last but not least, future studies can explore the impacts of "social nudge" on encouraging heat pump adoption.

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