Distributional Consequences of Policies for Electric Heat Conversion*

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June 13, 2023

PRELIMINARY: PLEASE DO NOT CITE OR DISTRIBUTE

Abstract

We study the adoption of air-source heat pumps for home heating. We estimate that 6%–8% of already-built homes converted to heat pumps during 2009–2020, while 25% of the new homes built during this period chose heat pumps. New adoptions concentrate among rural households in the South and West. Conversions are more diffuse, covering both urban and rural households in every region, and displacing whichever fuels are most prevalent in these places. Conversions and new adoptions are both sensitive to energy prices, accelerating when electricity prices fall or when natural gas, heating oil, or propane prices rise. In addition, we calculate the annual energy-cost savings from switching to a heat pump for a prototypical home in every U.S. census tract, based on local conditions, including current heating fuels, climate, and energy prices. We find massive variation, with low-income households in the Northeast and upper Midwest benefiting the most.

Key words: heat pumps, home heating, electrification

JEL classification numbers: Q40

*Acknowledgements: XXX.
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1 Introduction

Many states have adopted net-zero carbon emission goals. A substantial amount of renewable capacity has been added to the grid, reducing per-kWh emissions over the last 20 years (Holland, Mansur, Muller, and Yates 2020). As the average carbon content of U.S. electricity has decreased, attention has turned in recent years to reducing carbon emissions by electrifying home heating, hot water heating, and cooking. Currently, fossil-fuel combustion from these activities accounts for more than 10% of all U.S. carbon emissions (RMI 2021). To promote electrification, cities in California and elsewhere have implemented bans on new natural gas hookups, and California is poised to become the first state to ban natural gas use in new construction under the state's building code.

Efforts to electrify home heating have focused on electric heat pump technology, and many states have introduced policies to encourage or subsidize their use in residential settings (Nadel 2020). See Berg and Cooper (2020) for a complete list of state-level policies. This technology—which works like an air conditioner in reverse, transferring heat from the outside the home to inside the home—has made marked gains in efficiency over the last 10 years. New developments in heat pumps have expanded the range of climates for which electric heat pumps are suitable for residential heating, increasing the viability of this new technology. More efficient heat pumps have lower operating costs and are effective in heating down to 5 degrees Fahrenheit. Heat pump technology has advanced to the point that the technology is nearly synonymous with home heating electrification policy, as electric resistance (base-board) heating is largely uneconomical in most new applications. Furthermore, trends in electrification for home heating and home hot water heating indicate an increase in uptake, with electric heat pumps now comprising more than 50% of all residential heaters shipped by manufacturers (see figures 11, 12, and 13 in the appendix).

Little is understood about the decisions made by households to switch from fossil fuel to electricity for heating, or to switch heating technology to an electric heat pump.[1] Hlavinka, Mjelde, Dharmasena, and Holland (2016) examine the role of up-front incentives and advertising in driving heat pump adoption in the Pacific Northwest. Davis (2021b) focuses on new construction and finds that the 40-year decline in real electricity prices explains the vast majority of new heat pumps installed in new construction, suggesting that households are sensitive to electricity prices. However, owners of existing homes face a different set of costs and policies relative to new construction. For example, their duct-work may be designed to accommodate a particular heating technology in a particular location, or their existing furnaces may have many years of life remaining. How sensitive are these households to the upfront cost of electrification via a heat pump? To changes in electricity vs. natural gas prices? How will policies to promote electrification of home heating impact low-income households or other disadvantaged groups? Answering these questions will provide valuable

[1] We use "heating fuel" to refer to the fuel source, and "heating technology" to refer to the heating mechanism. We refer to electrification as a policy, but acknowledge that the primary heating technology used in electrification is the heat pump.

insights into the efficiency, effectiveness, and distributional impacts of policies—such as adoption subsidies or carbon taxes or changes in electricity rate design—designed to relieve energy burdens, reduce carbon emissions, or both. This is especially important given that new homes account for just 1% of housing stock in a given year, while existing homes that lack electric heating will last for decades if not centuries.

We address these questions by providing a range of evidence on heat-pump conversions. Our main analysis relies on the 2009, 2015, and 2020 waves of the Residential Energy Consumption Survey (RECS). We measure conversion rates via changes in the share of existing homes of the same vintage that use heat pumps, across different RECS waves—and by showing that homes that have recently replaced their heating equipment are more likely to have heat pumps, in the 2020 RECS. We explore correlates of heat-pump conversions and offer suggestive causal evidence on price-responsiveness. The RECS does not follow individual households over time. Thus, while we can infer net conversions from these data, we cannot identify underlying flows from one heating technology to another. Thus, we supplement the RECS with information from the American Housing Survey (AHS), which includes a short panel that allows us to measure these underlying flows. Neither data source provides detailed information on geography. Thus, we supplement this information with proprietary data on deliveries of HVAC equipment into local markets (zip codes) from an HVAC industry trade group. Finally, we calculate the private energy-cost savings from converting to a heat pump for a prototypical household in every U.S. census tract and explore the distributional implications.

Our analysis generates four main findings. First, for existing homes built before 2010 (92% of the housing stock), we estimate a 0.06–0.08 increase in the share using heat pumps as their primary heating technology over the last decade. Meanwhile, the share of new homes built in 2010 or later that use heat pumps is 0.25. Thus, recent growth in the overall share of heat pumps is dominated by conversions in existing homes ($0.92 \cdot 0.08 \approx 0.07$) rather than installations in new homes ($0.08 \cdot 0.25 \approx 0.02$). These conversions appear to be replacing natural gas and to a lesser extent heating oil.

Second, conversions are not strongly correlated with income, home ownership, home age, region, or urban vs. rural status. Conversions are somewhat more common at middle income levels and in the West. But we mostly find null results. This contrasts with newer homes, where heat pumps are more common among rural households and in the South. This also contrasts with other heating technologies, where both new construction and conversions exhibit strong correlations with home ownership, region, and urban vs. rural status.

Third, heat-pump conversions correlate strongly with cross-state differences in relative energy prices (heat pump vs. competing technology), even controlling for region, urban vs. rural, and household demographics. We complement these cross-sectional associations with a difference-in-differences design that more credibly delivers causal estimates, leveraging information on the timing of heat-pump installations and changes in state-level energy prices during the late 2010s. These estimates are less precise but suggest that a 10% increase in relative energy prices leads to a 0.03 increase in the share of existing homes with heat pumps. Meanwhile, among new homes, we find that a 10% increase in relative energy prices leads to a 0.09 increase in the share of homes with heat pumps. These results are consistent with the notion that switching costs are higher for existing homes than new construction.

Fourth, we calculate wide variation across U.S. zip codes in the private energy-cost savings from converting to a heat pump. This variation is driven by vast differences in heating demand (climate), baseline heating fuels, and energy prices, which interact to determine the benefits of switching. Projecting this variation onto zip-code level demographics, we infer that these benefits are highest for low- and medium-income households and people of European and Native American descent. These results are consistent with higher benefits for rural households, who disproportionately rely on costly propane and fuel oil for heating.

We contribute to a literature on choice of heating technology, nearly all of which focuses on new homes rather than conversions. Davis and Kilian (2011) estimate heating choice for new homes, showing that price controls on interstate sales of natural gas led to large welfare losses due to inefficient allocation across geography. Davis (2021b) explores the 70-year trend in home electrification for new homes, emphasizing the role of energy prices and to a lesser extent geography, climate, housing characteristics, and income. Davis (2021a) focuses specifically on heat pumps. Like us, he relies on the 2020 RECS and explores correlates of heat pump ownership in the cross section, i.e. the installed base which reflects both new construction and conversions over many decades. We differ by focusing specifically on recent heat-pump conversions, bringing in additional data, and developing methodologies to infer conversions from information on the timing of installation and estimate difference-in-difference style price responses. We show that conversions in the last decade account for 20% of the installed base and 80% of the annual flow of installations. These conversions are not well-explained by income or other demographics, echoing what Davis (2021a) finds for the installed base. We also estimate price responses but use a difference-in-difference style approach, showing that conversions respond strongly to energy prices but less so than for new-home installations.

The rest of this paper proceeds as follows. Section 2 describes our data sources. Section 3 describes our methods for inferring heat-pump conversions. Section 4 explores the relationship between heat-pump conversions and energy prices, income, and other factors. Section 5 estimates the private benefits of heat-pump conversion across U.S. zip codes and explores the distributional implications by race, income, and geography. Finally, section 6 concludes.

2 Data sources

This section describes the various datasets we use to study heat-pump conversions over the past decade.

2.1 Residential Energy Consumption Survey (RECS)

We construct our main sample using the RECS surveys from 2020, 2015, and 2009. The RECS is a regular survey fielded by the U.S. Energy Information Administration (EIA). It is designed to be a representative sample of household energy equipment and home energy consumption in the United States.

We focus on a household's reported main heating technology, which indicates the main fuel used for space heating, the type of space heating equipment (e.g. ductless heat pump or central gas furnace), and the age of this equipment. Age is given in ranges: less than 2 years, 2–4 years, 5–9 years, 10–19 years, and 20+ years. We use this information to identify when a home's heating equipment was most recently replaced. These questions are asked in each RECS wave. We combine all RECS waves from 2009–onward to form our main sample, resulting in repeated cross-section that includes over 50,000 households.

The RECS reports a variety of home characteristics, including a categorical variable for the decade in which the home was built—or vintage. The vintage categories are consistent across RECS waves: pre-1950, 1950–1959, 1960–1969, and so on. Thus, we are able to track changes in heating technology over time for homes of the same vintage, by comparing across RECS waves.

We also extract additional data to estimate the relationship between energy consumption and temperature, controlling for home size and vintage. These data include energy consumption used for space heating in millions of British thermal units (MMBTU), reported heating degree days (HDD) for the year, and home size in square feet (sqft). The HDD is calculated as the sum of the daily difference between the daily mean temperature and 65 degrees Fahrenheit. The RECS is widely known to "jitter" the HDD measure to ensure confidentiality of home location, but this is unlikely to cause substantial bias.

2.2 Energy prices

We obtain all energy prices from publicly available EIA data at the weekly level for propane and fuel oil, and at the monthly level for natural gas and electricity. When applicable, we use only data for residential customers. We convert all prices to dollars per MMBTU using EIA-published conversion factors. Different technologies convert raw MMBTUs to usable heat more or less efficiently. We assume 100% efficiency for electric-resistance heating, 95% efficiency for natural gas, 90% for fuel oil, and 85% for propane. Thus, we divide their respective energy prices by 1, 0.95, 0.9, and 0.85, to yield dollars per MMBTU of usable heat. A heat pump does not generate heat, but rather, it transfers outside heat, which allows it to achieve an efficiency rating greater than 100%. We assume an efficiency of 300% relative to electric-resistance heating. Thus, we divide the per-MMBTU electricity price by 3 to yield the effective energy price for a heat pump. In applications that require coarser data in the time dimension, we aggregate energy prices over the necessary time period.

The EIA reports electricity and natural gas prices monthly by state and utility. We alternatively use state and utility-level data as described below. The EIA reports propane and fuel oil prices weekly by state or by Petroleum Administration for Defense Districts (PADD) region during the heating months (September to March) each year. For states that do not explicitly report, we use the PADD price. These states tend to have low usage of the respective fuel. For instance, southern states use little fuel oil, and thus do not report weekly fuel oil prices. But they do use propane, which is reported. When annual prices are required for analysis, we take the average over all reported weeks for that year.

2.2.1 Matching to RECS data

When matching to our RECS data, we aggregate energy prices by state and year. The EIA reports annual residential natural gas prices by state, which they calculate as annual revenue divided by annual sales volume, yielding an annual average price. Meanwhile, the EIA reports monthly residential electricity prices for each state, which they calculate as monthly revenue divided by monthly sales volume, yielding a monthly average price. We do not calculate the straight average of this monthly price, since doing so would weight low-demand months and high-demand months equally and interact strangely with utility pricing schedules.[2] Rather, we divide annual revenue by annual sales volumes (also reported by EIA), yielding an average price for the whole year, same as for natural gas.

Annual revenues for both electricity and natural gas include fixed charges. Thus, the average prices we use will tend to overstate the variable prices that in theory should matter for heating technology choices. In future iterations of this paper, we propose to back out variable and fixed charges by regressing monthly revenues on monthly sales volumes separately for each state, as in Davis and Muehlegger (2010).[3]

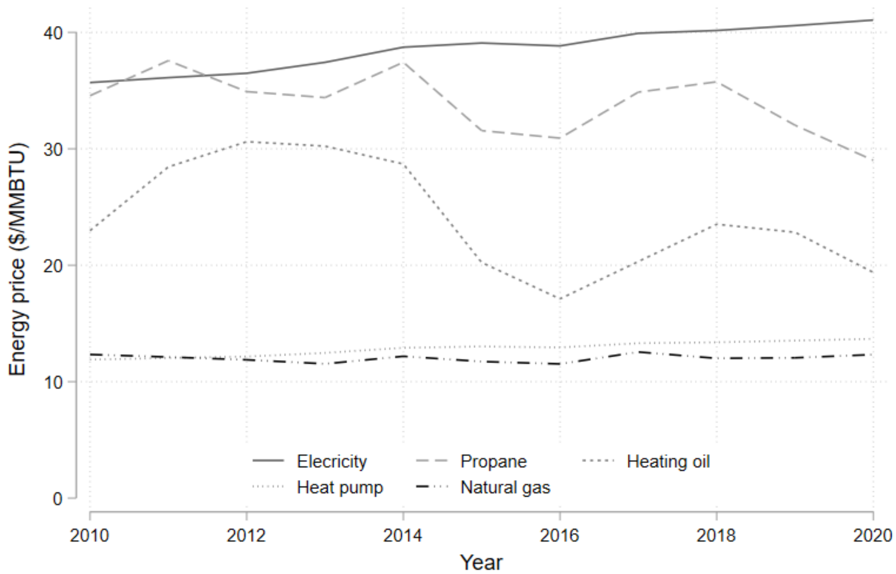
The EIA reports weekly propane and heating oil prices for many states and PADDs, as described above. We calculate the straight average of these prices for the year. These prices are only reported for the winter heating months. Thus, the unweighted average will tend to reflect energy costs most relevant for home heating.

Figure 1 shows the annual means of our energy prices across all states (unweighted) for 2010–2020. Prices for natural gas, heating oil, propane, electricity (resistance), and heat pumps are all expressed in dollars per MMBTU of usable heat, i.e. accounting for different energy units and efficiency levels across these technologies. Note that electric-resistance heating has the costliest energy on average, followed by propane and heating oil. Natural gas is the cheapest energy overall, but only by a hair: heat pumps are a very close

[2] Monthly revenues include both variable and fixed charges. Thus, average prices will tend to be lowest during periods of high demand and highest during periods of low demand, as the fixed charges are averaged over more or less quantity. Taking a straight average could lead to bizarre results in such cases. Indeed, if demand were zero in some month, then the average price for that month would be infinitely high.

[3] But note that (Ito 2014) shows that consumers respond to average prices rather than marginal prices in the context of block-tiered pricing for electricity.

Figure 1: *Energy prices for different heating technologies*



Note: This figure shows energy prices in dollars per MMBTU of usable heat for natural gas, heating oil, propane, electricity (resistance), and heat pumps. Prices are annual means across all states (unweighted) of the annual state average prices described in this section. Data source: Author calculations based on EIA data.

second. Electricity is the most expensive energy in dollars per MMBTU of raw energy (top line). Yet the effective energy cost of a heat pump is just 1/3 as high due to its superior efficiency. These averages mask substantial variation in prices across states and over time within states. We use this price variation below to estimate price responses.

2.2.2 Energy prices for calculating distributional impacts

In section 5 we calculate the expected energy-cost savings from heat pump adoption by census tract based on average energy prices for 2014–2018. This analysis requires spatially explicit energy prices, ideally capturing variable rather than average prices. We continue to use state-level propane and heating oil prices from EIA as described above (or PADD when state is not available). But we use more refined measures of natural gas and electricity pricing available from EIA, as described here.

We start by matching census tracts to electricity and gas utility service territories using maps published in the Homeland Infrastructure Foundation-Level (HIFLD) Database.[4] These maps are compiled from EIA filings and maps published by utilities themselves. When a census tract overlaps with more than one utility area, we use the larger utility (as measured by number of customers).

[4]See here: https://hifld-dhs-gii.gov/HIFLD

We obtain electricity prices for the majority of electric utilities from EIA Form 861M, which reports monthly revenue and sales quantity by customer type for large utilities, plus a residual "state adjustment" that captures the non-reporting utilities. We estimate variable price by regressing monthly revenues on monthly sales quantities separately for each utility and quarter, using only data for residential customers. Each OLS regression is centered on a given quarter (February, May, August, or November) and includes the 12 months before and after for a total of 25 monthly observations. We weight observations using a triangular kernel. We calculate average variable price as the mean of our quarterly slope estimates for 2014–2018. For electric utilities that do not report monthly on EIA Form 861M, we apply the same procedure to the "state adjustment" as if it were a single utility.

We augment the EIA Form 861M data for the state of Georgia with survey data from the Georgia Public Services Commission (GPSC).[5]. The GPSC surveys Georgia's regulated utilities annually, recording bill totals for hypothetical consumption levels of 500, 1000, 1500, and 2000 kWh. This survey is performed twice each year, generating a "winter" and a "summer" rate for each utility. We regress hypothetical revenues on consumption levels (four data points) for each utility, year, and season. We calculate average variable price as the mean of our slope estimates for 2014–2018. When available, we use these average prices to replace our similar estimates based on EIA Form 861M. The GPSC reports survey results for 92 utilities, of which 20 match to HIFLD-reported utility service areas.[6]

We calculate annual natural gas prices for all utilities that report on EIA Form 176. Filed annually, EIA Form 176 records total revenue and sales volume for each utility (with multi-state utilities reporting separately for each state). We calculate natural gas prices as revenue divided by sales volume, yielding a utility-specific average price.[7] For natural gas utilities that do not report on EIA Form 176, we use the state-average price for natural gas as described in the previous subsection.[8]

2.3 American Housing Survey (AHS)

Coming soon ...

2.4 Proprietary HVAC distribution data

To examine market shares by type of heating equipment, we partner with an HVAC distribution trade group which generously provided extensive data on distributor shipments of heating equipment. The proprietary data consists of over 7,000,000 delivered HVAC units, the unit model numbers, the date of delivery, and the zip code of delivery. The zip code of delivery allows us to develop spatially fine-grained market shares not

[5] See here: https://psc.ga.gov/utilities/electric/residential-rate-survey/

[6] Remaining unmatched utilities do not have unique, exclusive territories or do not appear in HIFLD maps.

[7] We would like to estimate variable price using variation in monthly revenue and sale quantity, as we do for electricity. But EIA Form 176 only reports annual data.

[8] Unlike EIA Form 861M for electricity, EIA Form 176 for natural gas does not report total revenue and sales quantity for the "state adjustment" areas.

previously available to researchers.

We focus our attention to a subset of the data that is most complete and relevant to our question. While the proprietary distributor data covers the period 2010 to 2022, we isolate the years 2015-2019, when coverage across the number of distributors is highest, and prior to the market interruptions associated with the COVID pandemic. We also focus on three regions: the west, the southeast, and the eastern mid-west, as these areas have the most complete coverage. For a distributor's sales data to appear in the sample, they must voluntarily submit sales on a monthly basis. Distributors in these regions have the highest participation rate. Finally, we restrict the sample to residential HVAC equipment, which comprises around 70% of the total reported sales in the proprietary data.

To assemble a market-level panel of HVAC shipments and market shares of heat pumps, we first match reported model numbers to known models registered with the American Heating and Refrigeration Institute (AHRI), which represents the manufacturers of nearly all HVAC units sold in the United States, regardless of country of origin. AHRI is both a manufacturer's trade group and a certification body that provides independent testing of HVAC models under an ISO-compliant system, and issues the AHRI "certified" markings for final products. The certification process measures and publishes each model's performance and efficiency; it is the AHRI certification that establishes a unit's Seasonal Energy Efficiency Rating (SEER), it's Annual Fuel Utilization Efficiency (AFUE), and other commonly-used efficiency measures. Nearly all HVAC units sold in the United States are AHRI-certified, and AHRI certification standards are incorporated by reference into the U.S. Code of Federal Regulations.[9] Once matched, unit type is extracted, and market shares for heat pumps are constructed as the fraction of all residential heating-capable units that are certified under any of the AHRI Heat Pump programs.

The proprietary sample data contains 3,424,099 total HVAC units sold during the sample period. Many distributors have provided sale price for each unit shipped in the data. Over the 2,490,572 units reported with price, the total value of shipments is $2,244,579,597.

2.5 Other data

Section 5 merges income and race shares at the zip code level to measure correlations between potential savings from heat pump adoption and sociodemographic variables. Income and race are obtained from the 5-year American Community Survey (ACS) dataset for 2018. Tract-level variables are extracted and aggregated to the zip code level, weighting by area of overlap. Shares of race and income bins are calculated using the aggregate household counts.

Section 5 models heating consumption in MMBTU as a function of heating degree days (HDD). To predict heating consumption outside the RECS sample, we use county-level five-year average HDD reported by the

[9] 10 CFR Part 430

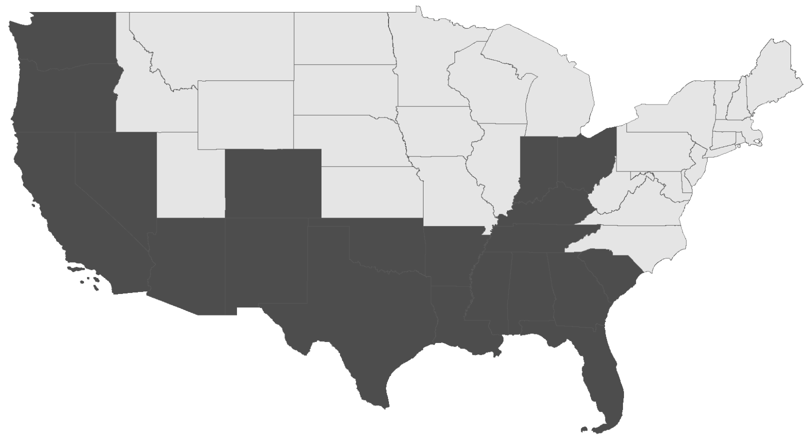


Figure 2: *States included in proprietary data sample*

National Oceanic and Atmospheric Administration (NOAA) National Center for Environmental Information (NCEI).

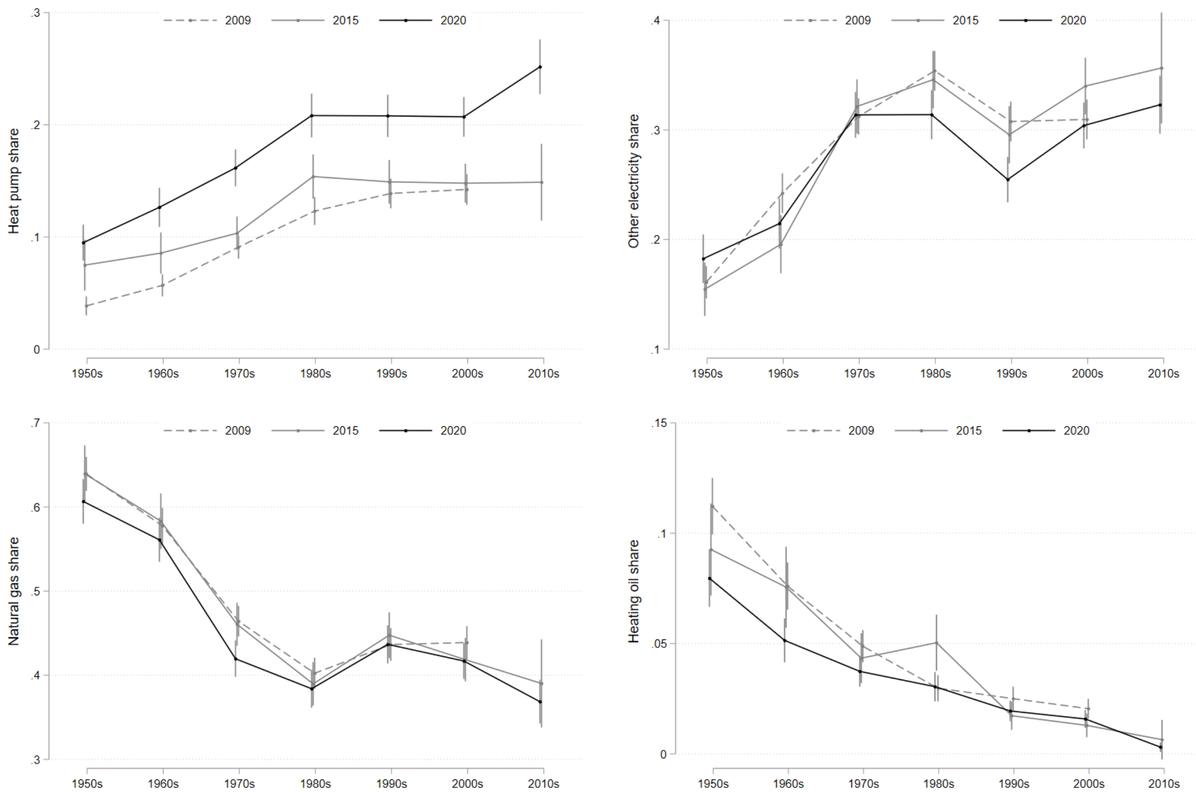
3 Trends in heat-pump conversions

In this section we estimate trends in heat-pump conversions over the last decade. We infer conversions in three distinct ways: (i) from increases over time in the share of existing homes that rely on heat pumps, (ii) from the fact that homes with newer heating equipment are more likely to rely on heat pumps, and (iii) by directly measuring changes in heating equipment over time for individual homes. The first two approaches only allow us to infer net conversions. For example, suppose we observe a 10% increase in the share of existing homes with heat pumps and a 10% decrease in the share using natural gas. These changes might imply 10% of homes converting from natural gas to a heat pump. Or they might imply 15% of homes converting from natural gas to a heat pump, 5% converting from propane to natural gas, and 5% converting from a heat pump to propane. Thus, we only estimate net conversions in aggregate. In contrast, the third approach allows us to directly measure transitions from one heating technology to another.

3.1 Inferring conversions across RECS waves

We identify net conversions over the last decade based on changes in the share of existing homes that use heat pumps as their main heating technology. We start with a pooled cross section of the RECS waves from 2009, 2015, and 2020. We restrict the sample to households whose homes were built in 2009 or earlier and that heat their home using air-source heat pumps, other forms of electricity (mainly baseboard and central

Figure 3: *Heating technology by RECS wave and home vintage*



Note: This figure shows the share of households that rely on an air-source heat pump, other forms of electricity, natural gas, or heating oil conditional on home vintage for each RECS wave. In constructing the figure, we restrict the sample to households that heat their home with electricity, natural gas, heating oil, propane, or wood, and we account for RECS sampling weights. Data source: RECS 2009, 2015, and 2020.

electric resistance heating), natural gas, heating oil, propane, or wood. Figure 3 plots heating technology shares conditional on home vintage across the three RECS waves. The figure shows that homes are more likely to have heat pumps and less likely to have other technologies in each subsequent wave. We interpret these changes as net conversions in heating technology. Heat-pump shares increase across all vintage of homes. Meanwhile, the share of homes using other forms of electricity falls mainly among newer homes, while the share of homes using natural gas and heating oil falls mainly among older homes. This finding foreshadows many of our later results: heat pump conversions are widespread but the replaced technologies vary by age and location, depending on the installed base of alternative technologies.

Formally, we measure conversions relative to 2009 via regression using a linear probability model:

$$y_i = \beta_0 + \beta_1 \text{RECS15}_i + \beta_2 \text{RECS20} + controls_i + \epsilon_i, \tag{1}$$

where: y_i is a binary 0/1 variable indicating whether household i uses a given method (heat pump, other

Table 1: *Regression results: heating technology by RECS wave*

	(1) HP	(2) Elec	(3) Gas	(4) Oil	(5) Prop
Constant	0.089***	0.259***	0.508***	0.068***	0.051***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
RECS 2015	0.014***	-0.004	0.007	-0.015***	-0.007*
	(0.004)	(0.006)	(0.007)	(0.003)	(0.003)
RECS 2020	0.064***	-0.009	-0.018**	-0.022***	-0.008**
	(0.004)	(0.005)	(0.006)	(0.002)	(0.003)
Observations	49584	49584	49584	49584	49584

Note: This table presents coefficient estimates from equation (1) on pooled data for RECS waves 2009, 2015, and 2020. The dependent variable is an indicator for a given heating technology. Each column corresponds to a different technology. Observations are weighted by RECS sampling weights. Standard errors in parentheses are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: RECS 2009, 2015, and 2020.

electric, natural gas, heating oil, or propane) as their main heating technology; $RECS15$ and $RECS20$ are dummy variables indicating the 2015 and 2020 waves; $controls$ is a set of optional controls; ϵ_i is an idiosyncratic error; and the β's are parameters to be estimated. We estimate this model separately for every heating technology.

Table 1 reports the OLS coefficient estimates without the optional controls. The constant term reports heating fuel shares in 2009, while the coefficients on the 2015 and 2020 dummies indicate changes relative to this base year.[10] The coefficient on the 2020 dummy in the first column indicates a 0.064 increase in the share of existing homes that use heat pumps. Given the starting share of 0.089, this represents a net conversion rate of $0.064/(1-0.089) \approx 7\%$ over one decade. Meanwhile, the other columns indicate net conversions away from electricity, natural gas, heating oil, and propane. The table omits a tiny fraction of households that heat with wood or other technologies. Conversion rates barely budge with the inclusion of controls for census region and home vintage.

For comparison, table 2 reports choices of heating technology for recently built homes. The row labeled RECS 2009 reports heating technology shares in 2009 for homes built in 2000–2009, while the row labeled RECS 2020 reports shares in 2020 for homes built in 2010-2020. The share of new homes relying primarily on a heat pump is 0.25 in 2020 compared to just 0.14 in 2009. Meanwhile, the share relying on natural gas is 0.37 in 2020 compared to 0.44 in 2009. This evolution away from natural gas and toward heat pumps may reflect changes in where new homes are being built, along with changes in heating technology over time

[10] Table 8 in the appendix shows the same information in levels: heating technology shares separately for each RECS wave.

Table 2: *Share of new homes with different heating technologies*

	(1) HP	(2) Elec	(3) Gas	(4) Oil	(5) Prop
RECS 2009	0.142***	0.310***	0.439***	0.021***	0.072***
	(0.007)	(0.009)	(0.010)	(0.002)	(0.006)
RECS 2020	0.252***	0.323***	0.369***	0.003**	0.043***
	(0.012)	(0.013)	(0.013)	(0.001)	(0.005)
Observations	4916	4916	4916	4916	4916

Note: This table reports the estimated share of new homes that rely on various heating technologies in 2009 and 2020. New homes in 2009 were built in 2000–2009, while new homes in 2020 were built in 2010–2020. Standard errors in parentheses are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: RECS 2009 and 2020.

within a given location.

So which is more important for explaining the overall growth in heat-pump share: new or existing homes? Only 6.4% of existing homes switched to heat pumps during the 2010s, while 25% of new homes had heat pumps. Yet new homes accounted for just 8% of all homes in 2020, while old homes accounted for 92%. Thus, conversions in old homes contributed $0.064 \cdot 0.92 \approx 6\%$ to the overall share of homes with heat pumps in 2020, while new homes contributed just $0.08 \cdot 0.25 \approx 2\%$. Thus, three quarters of the growth over the last decade is due to heat-pump conversions in existing homes.

3.2 Inferring heat pump conversions within the RECS 2020 wave

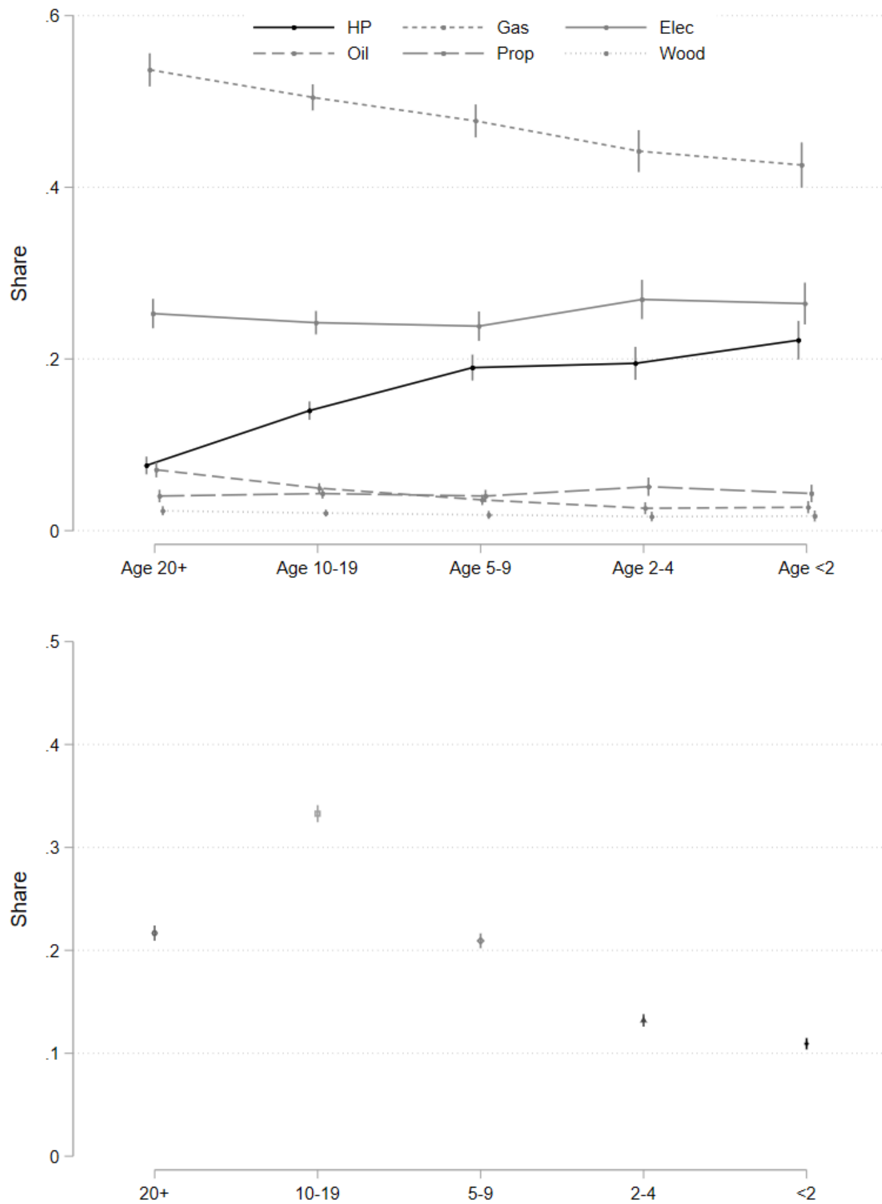
We identify recent conversions in heating technology within the 2020 RECS based on the age of the primary heating equipment. Intuitively, if heat pumps are more prevalent among existing homes with new heating equipment, we infer net conversions toward heat pumps and away from other technologies.

To illustrate, figure 4 plots the share of different heating technologies conditional on the reported age of the heating equipment (top panel) along with the distribution of reported age (bottom panel). The figure shows that heat pumps are more common in homes with newer equipment, while other technologies are less common. We have again restricted the sample to households whose homes date to 2009 or earlier and that use heat pumps, other forms of electricity, natural gas, heating oil, propane, or wood. Note that we observe these households in 2020. Thus, equipment less than 10 years implies that the home's heating equipment was replaced sometime after 2009. Differences in heating technology for homes with new vs. old equipment therefore represent a net conversion in heating technology.

Formally, we measure conversions within the last decade via regression using a linear probability model:

$$y_i = \beta_0 + \beta_1 I(\text{Age} < 10)_i + controls_i + \epsilon_i, \quad (2)$$

Figure 4: *Heating technology by equipment age*



Note: The top panel of this figure shows the share of households that rely on an air-source heat pump, other forms of electricity, natural gas, heating oil, propane, or wood conditional on the estimated age of their main heating equipment. The bottom panel shows the distribution of heating equipment age. In constructing the figure, we restrict the sample to households that heat their home using electricity, natural gas, heating oil, propane, or wood, and we account for RECS sampling weights. Data source: RECS 2020.

where: y_i is a binary 0/1 variable indicating whether household i uses a given method (heat pump, other electric, natural gas, heating oil, or propane) as their main heating technology; $I(\text{Age} < 10)$ is a dummy

Table 3: *Regression results: heating technology by equipment age*

	(1) HP	(2) Elec	(3) Gas	(4) Oil	(5) Prop
Constant	0.115***	0.246***	0.517***	0.058***	0.042***
	(0.004)	(0.005)	(0.006)	(0.003)	(0.002)
Age < 10	0.084***	0.007	-0.063***	-0.027***	0.002
	(0.007)	(0.008)	(0.009)	(0.003)	(0.004)
Observations	16002	16002	16002	16002	16002

Note: This table presents coefficient estimates from equation (2) using the 2020 RECS. The dependent variable is an indicator for a given heating technology. Each column corresponds to a different technology. Observations are weighted by RECS sampling weights. Standard errors in parentheses are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: RECS 2020.

variable indicating that the heating equipment is 0–9 years old; *controls* is a set of optional controls; ϵ_i is an idiosyncratic error; and the β's are parameters to be estimated. We estimate this model separately for each heating technology.

Table 3 reports the OLS coefficient estimates without the optional controls. The coefficients on the constant term yield heating technology shares for homes whose equipment is at least 10 years old, i.e. installed in 2009–2010 or earlier. Note that these coefficients are very similar to the constant terms in table 1, corresponding to fuel technology shares in the 2009 RECS for homes built in 2009 or earlier. Meanwhile, the coefficients on the $I(\text{Age} < 10)$ dummy indicate the change in heating technology shares for newer equipment relative to older equipment. Zero coefficients would indicate no net change in heating technology as older equipment replaces newer equipment. In fact, we see a 0.084 net increase in the share of heat pumps. Given the starting share of 0.115, this represents a net conversion rate of $0.084/(1 - 0.115) \approx 9.5\%$ over one decade. Meanwhile, the other columns indicate net conversions away from natural gas and heating oil, with close to zero net conversions for other forms of electricity and propane. These numbers indicate that conversions since 2009–2010 contributed $0.084 \cdot 0.92 = 7.7\%$ to the overall share of homes with heat pumps in 2020.

Below we seek to explain heat-pump conversions as a function of energy prices, income, and other factors. To do this, we leverage information on the age of primary heating equipment in the 2020 RECS, since this survey identifies state of residence and therefore allows us to match to state-level energy prices. Unfortunately, while all RECS waves indicate the census division in which a home is located, prior RECS waves only identify the specific state for a handful of large states, e.g. Texas and California. Further, income categories are not comparable across RECS waves due to inflation and changing income categories. Thus, we are unable to correlate conversions with energy prices and incomes by comparing across different RECS waves.

3.3 Inferring conversions in the AHS

Coming soon ...

4 Correlates of heat-pump conversions

In this section we explore how heat-pump conversions correlate with energy prices, income, and other factors. We begin by showing graphical evidence based on cutting the sample in various dimensions. We then interact heating equipment age with various covariates to estimate what amounts to a cross-sectional regression of heat-pump conversions on energy prices and controls. We conclude with a difference-in-differences inspired regression that leverages variation in timing of recent heat-pump installations to yield more credible causal estimates.

4.1 Split-sample approach

We continue to focus on households in the 2020 RECS whose homes were built in 2009 or earlier and that primarily heat their home using heat pumps, other forms of electricity, natural gas, heating oil, propane, and wood. We estimate the following linear probability model:

$$y_i = \beta_0 + \beta_1 I(\text{Age} < 2)_i + \beta_2 I(\text{Age 2–4})_i + \beta_3 I(\text{Age 5–9})_i + controls_i + \epsilon_i, \tag{3}$$

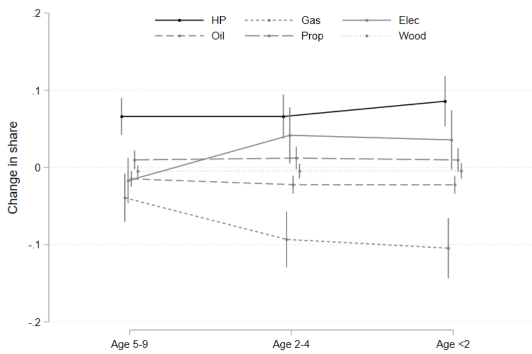
where everything is the same as before but we have replaced the single $I(\text{Age} < 10)$ dummy with a more detailed set of age-range dummies. We again estimate this model separately for each heating technology. We estimate the model for the full sample, as well as for various sub-samples split by demographics and location.

Figure 5 shows the first set of OLS estimation results. The figure shows coefficients on the age-range dummies (relative to homes with heating equipment age 10+ years), with sloped lines connecting coefficient estimates for different age ranges, along with vertical lines representing 95% confidence intervals. Comparing coefficients on the left vs. right, we detect no large differences in recent conversions to heat pumps for low-income vs. high-income (splitting at median income), urban vs. rural, or renter vs. owner-occupied households. In fact, the figures on the left and right look strikingly similar. The only notable difference is that households in urban areas (middle left) mainly show a decrease in reliance on natural gas, while households in rural areas (middle right) mainly show a decrease in heating oil, reflecting differences in baseline heating technologies.

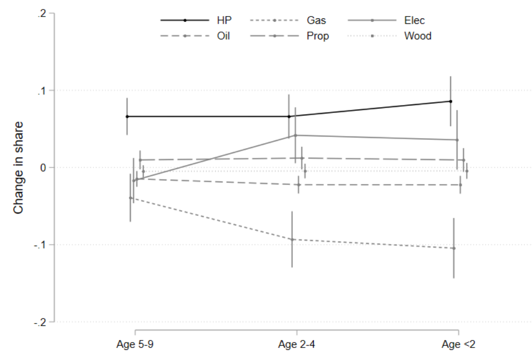
Figure 6 continues by showing OLS estimation results separately for each of four census regions: Northeast, Midwest, South, and West. Conversions are somewhat higher in the South and West than in the Northeast

Figure 5: *Heating technology by equipment age and demographics*

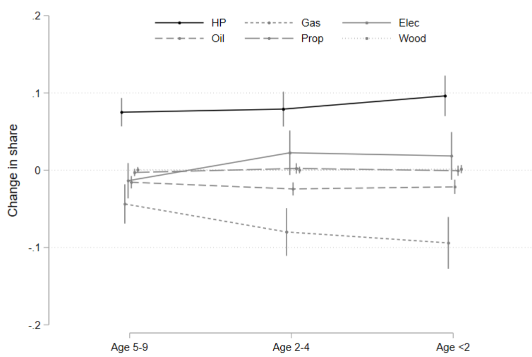
(a) Low income



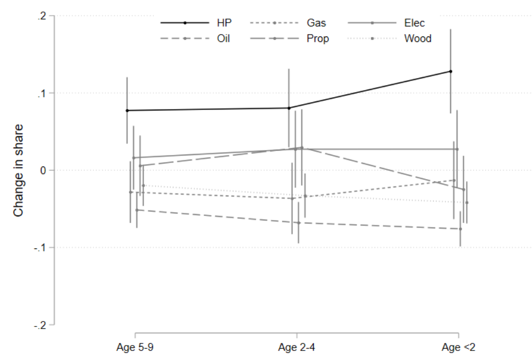
(b) High income



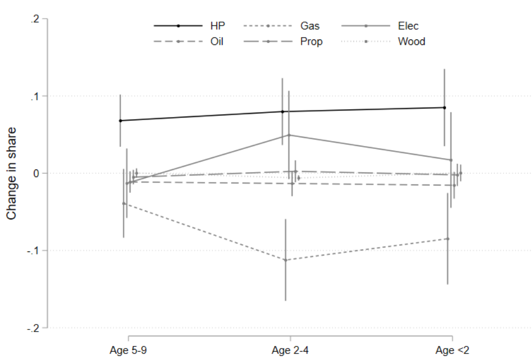
(c) Urban



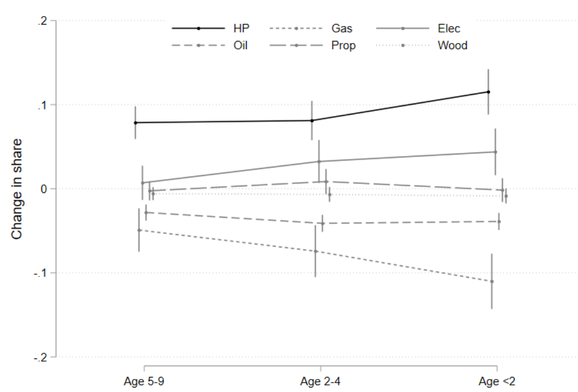
(d) Rural



(e) Renter

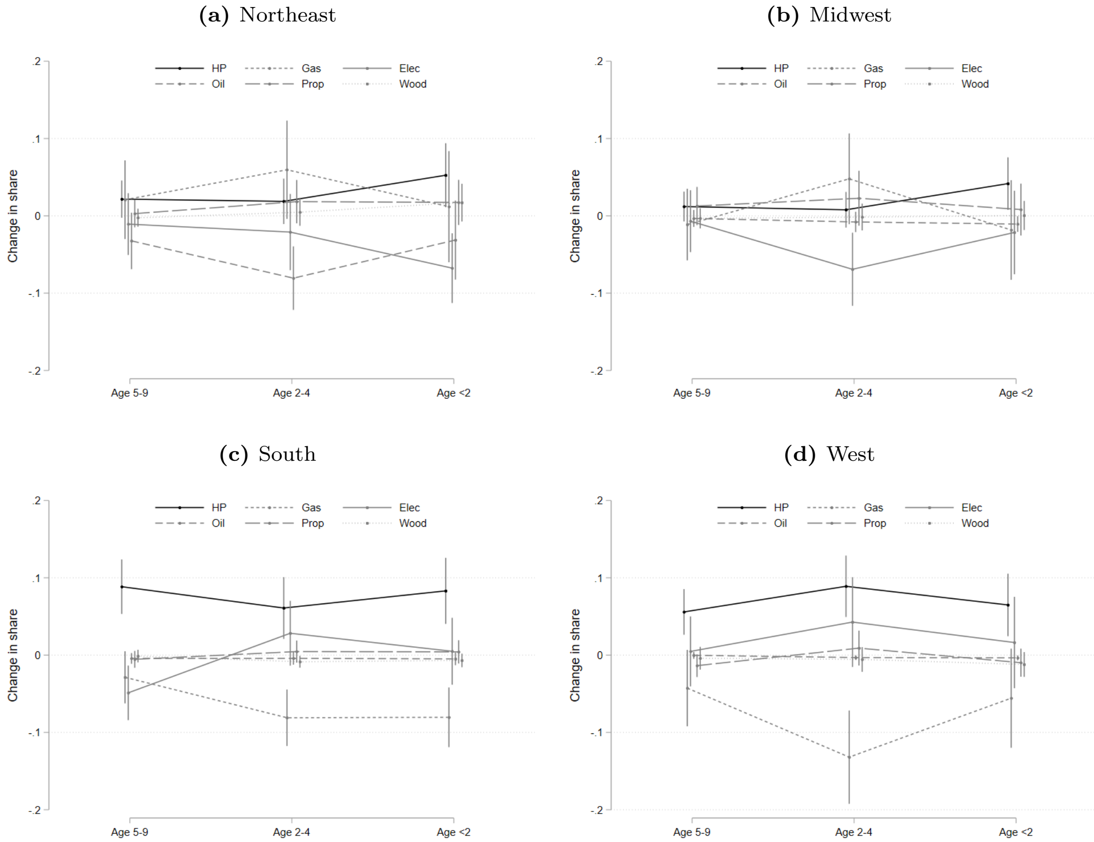


(f) Home owner



Note: This figure shows OLS estimation result for heating technology indicators regressed on equipment age dummies separately for low vs. high income, urban vs. rural, and renter vs. owner-occupied households. Marker symbols indicate coefficient estimates, with sloped lines connecting coefficient estimates for each heating technology. Vertical bars represent 95% confidence intervals based on heteroskedasticity-robust standard errors.

Figure 6: *Heating technology by equipment age and census region*



Note: This figure shows OLS estimation result for heating technology indicators regressed on equipment age dummies separately for each of four census regions: Northeast, Midwest, South, and West. Marker symbols indicate coefficient estimates, with sloped lines connecting coefficient estimates for each heating technology. Vertical bars represent 95% confidence intervals based on heteroskedasticity-robust standard errors.

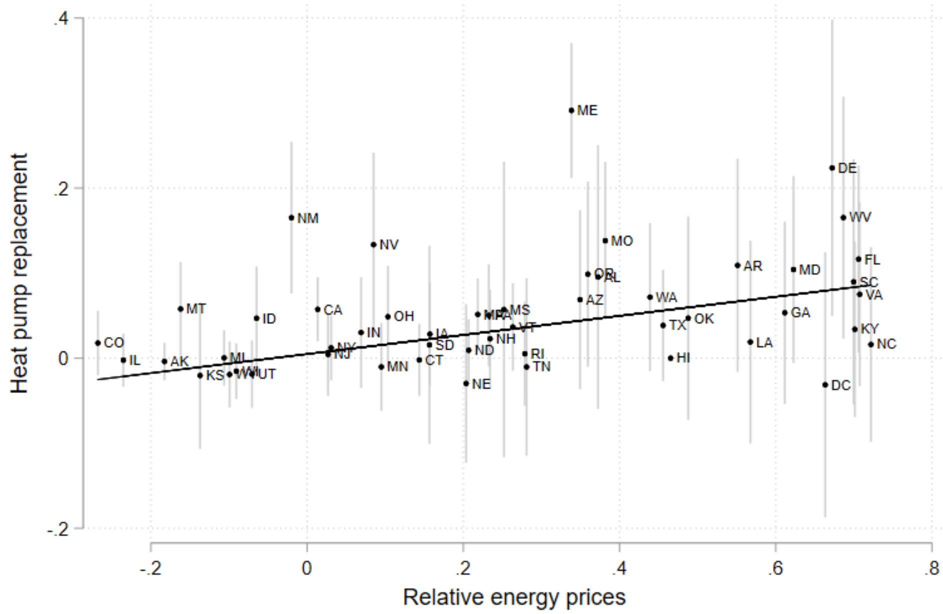
and Midwest. But more striking are the differences in what competing technologies correspondingly see net declines: heating oil and some electricity in the Northeast, electricity in the Midwest, and natural gas in the West and South.

Finally, to explore how heat-pump conversions relate to energy prices, we also use a split-sample approach. For each state, we regress an indicator variable for heat pump as primary heating technology on two age-range dummies:

$$hp_i = \beta_0 + \beta_1 I(\text{Age 0–4})_i + \beta_2 I(\text{Age 5–9})_i + controls_i + \epsilon_i, \tag{4}$$

where the coefficient β_1 measures conversions occurring within the last four years. For this exercise, we desire a single coefficient estimate. Respondents report the age of their heating equipment with some imprecision. Thus, we focus on newer equipment, where respondents are more likely to report the timing accurately,

Figure 7: *Heat pump conversions vs. energy prices by state*



Note: This figure plots the estimated coefficient on the I(Age 0–4) dummy estimated separately for each state vs. relative energy prices in each state. We measure relative energy prices in each state as: $\ln p_r = \sum_{j \neq hp} \theta_j \ln p_j / \sum_{j \neq np} \theta_j - \ln(p_{hp})$, where p_j is the mean per-MMBTU price of energy for heating technology j in a state and θ_j is the corresponding share of the state's households that report using that technology in RECS waves 2009 and 2015. That is, we measure relative energy prices as the weighted average of log energy prices for alternative technologies minus the log energy price for a heat pump. We compute the per-MMTBU means for 2010–2019 prior to taking logs and weighting.

presumably yielding a more accurate conversion rate.

Figure 7 plots the resulting coefficient estimates vs. relative energy prices in each state. The the black dots represent the state-by-state point estimates, while the vertical bars represent the corresponding 95% confidence intervals. The figure also shows an OLS fitted line through the point estimates, with the point estimates weighted by households in the 2020 RECS sample. The fitted line implies that a one-unit increase in log relative energy prices is associated with a 0.11 increase in heat pump replacement in recent years. Of course, this cross-sectional association does not control for other drivers of conversions, whether observed or not. We therefore turn to a controlled regression below.

4.2 Interactions with energy prices and demographics

We now explore how heat-pump conversions correlate with energy prices conditional on income and other factors. To do this, we interact the dummy variable for heating equipment age with energy prices as well as dummy variables for different categories of income, renter vs. owner-occupied, urban vs. rural, census region, and home vintage. We again focus on heating equipment that is less than four years old to ensure that we are measuring conversions and not original equipment, given the imprecision with which respondents report equipment age. We continue to focus on homes built in 2009 or earlier in the 2020 RECS. We estimate the following linear probability model:

$$y_i = \beta_0 + \beta_1 I(\text{Age 0–4})_i + \beta_2 I(\text{Age 5–9})_i + \gamma' X + \delta' X_i \cdot I(\text{Age 0–4})_i + \epsilon_i, \tag{5}$$

where y_i is again a 0/1 an indicator for a given heating technology. Note that we have added controls for state-level energy prices and individual-level observables (X) along with interactions between the age dummy and these observables ($X_i \cdot I(\text{Age 0–4})$), where γ and δ are vectors of coefficients on the covariates and their interactions with the new equipment dummy. We are mainly interested in the coefficients on the interactions (δ), which capture predictable differences in the rate of heating technology conversion by energy prices and other factors.

Table 4 reports the OLS coefficient estimates (δ) on the interactions between the new equipment dummy and the observed covariates ($X_i \cdot I(\text{Age 0–4})$). We suppress the coefficients on the new equipment dummy and the covariates themselves to focus on the interaction terms.[11]

Column (1) is the regression for heat pump conversions. The first coefficient indicates that a 10% increase in heat-pump electricity prices is associated with a 0.009 decrease in the share of households that convert to a heat pump over the last 4 years. Meanwhile, a 10% increase in other-technology energy prices (weighted average of log electricity, log natural gas, log heating oil, and log propane prices) is associated with a 0.016 increase in the share of households that convert to a heat pump. Note that the baseline rate of conversion for equipment age 0–4 is 0.092 (see table 9 in the appendix). Thus, these effects imply conversion elasticities of $0.009/0.092/0.1 \approx 1$ and $0.016/0.092/0.1 \approx 1.7$ with respect to energy prices. Thus, these are economically meaningful effects.

Echoing our split-sample results above, with few exceptions, we do not find statistically large differences in the rate of heat pump conversion by income, census region, urban vs. rural, renter vs. owner-occupied, or home vintage. Instead, we find differences for other technologies: conversions away from electricity for homes built in the 1970s through the 1990s, conversions away from natural gas in the South and West and toward natural gas in rural areas (presumably due to expanding infrastructure), conversions away from heating oil in rural areas and toward heating oil outside the Northeast. These other technologies are generally less responsive to energy prices.[12]

[11] Note that all variables in this table are interactions between the new equipment dummy and the indicated variable, even though the variable labels do not explicitly show the interaction with equipment age.

[12] Note that we measure "self" and "other" energy prices separately for each technology, e.g. the "other" price for natural gas is a weighted average of electricity, propane, and heating oil prices.

Table 4: *Regression results: heating technology conversions in old homes*

	(1) Heat pump	(2) Electric	(3) Natural gas	(4) Heating oil	(5) Propane
ln(pself)	-0.094	0.015	-0.005	0.001	0.001
	(0.057)	(0.066)	(0.045)	(0.001)	(0.003)
ln(pother)	0.162***	-0.024	0.002	-0.026	-0.030
	(0.049)	(0.041)	(0.030)	(0.015)	(0.025)
$30-39k	0.031	-0.024	0.016	-0.011	-0.017
	(0.029)	(0.038)	(0.037)	(0.012)	(0.015)
$40-49k	0.045	-0.056	0.032	-0.007	0.008
	(0.035)	(0.040)	(0.037)	(0.013)	(0.017)
$50-59k	0.051	-0.072	0.020	-0.012	0.003
	(0.031)	(0.037)	(0.037)	(0.013)	(0.016)
$60-74k	0.115***	-0.099**	-0.009	0.003	-0.003
	(0.030)	(0.034)	(0.034)	(0.012)	(0.015)
$75-99k	0.049	-0.077*	0.067*	-0.015	-0.015
	(0.027)	(0.033)	(0.033)	(0.011)	(0.014)
$100-149k	0.048	-0.049	0.034	-0.016	-0.012
	(0.027)	(0.031)	(0.032)	(0.011)	(0.014)
$150k+	0.024	-0.041	0.029	-0.031**	0.013
	(0.027)	(0.032)	(0.033)	(0.011)	(0.015)
Midwest	0.038	-0.018	-0.011	0.037*	-0.017
	(0.025)	(0.036)	(0.035)	(0.017)	(0.020)
South	-0.029	0.071	-0.089**	0.052**	-0.003
	(0.031)	(0.037)	(0.029)	(0.018)	(0.016)
West	0.055*	0.054	-0.100**	0.041*	-0.009
	(0.025)	(0.039)	(0.036)	(0.018)	(0.018)
Rural	0.010	-0.030	0.078***	-0.037***	0.001
	(0.021)	(0.022)	(0.022)	(0.010)	(0.018)
Owner	0.009	0.024	-0.033	-0.017*	0.009
	(0.020)	(0.025)	(0.024)	(0.008)	(0.008)
1950s	0.006	-0.000	-0.039	0.024	-0.012
	(0.024)	(0.034)	(0.037)	(0.017)	(0.014)
1960s	0.023	-0.054	0.028	0.007	-0.001
	(0.027)	(0.034)	(0.038)	(0.014)	(0.015)
1970s	0.021	-0.063*	0.041	0.018	-0.007
	(0.024)	(0.032)	(0.033)	(0.013)	(0.015)
1980s	0.059*	-0.087**	0.025	0.017	-0.012
	(0.027)	(0.033)	(0.034)	(0.012)	(0.015)
1990s	0.004	-0.071*	0.067*	0.024*	-0.015
	(0.025)	(0.032)	(0.034)	(0.011)	(0.017)
2000s	0.033	-0.040	0.016	0.024*	-0.021
	(0.029)	(0.035)	(0.035)	(0.011)	(0.015)

Note: This table presents coefficient estimates from equation (5). The sample is homes built in 2009 or earlier. The dependent variable is an indicator for a given heating technology. Each column corresponds to a different technology. The table only reports coefficients on the interactions between the $I(\text{Age } 0-4)$ dummy and the variables indicated in the table; main effects are not reported here. Observations are weighted by RECS sampling weights. Standard errors in parentheses are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: RECS 2020.

For comparison, we run a similar set of regressions focused on new homes built in 2010 or later:

$$y_i = \beta_0 + \delta' X + \epsilon_i, \tag{6}$$

where X captures energy prices and other covariates. Note that we do not interact these variables with age dummies, since we assume mostly original equipment for new homes built in the last 10 years.[13]

Table 5 reports the OLS coefficient estimates. Heating technology choices in new homes are generally more price-sensitive than conversions in existing homes. For heat pumps, a 10% increase in electricity prices is associated with a 0.006 decrease in the share of new homes choosing heat pumps, while a 10% increase in energy prices for alternative technologies is associated with a 0.023 increase. Relative to the baseline choice share of 0.25, these estimates imply elasticities of $0.006/0.25/0.1 \approx 0.2$ and $0.023/0.25/0.1 \approx 0.9$. Thus, the absolute change in share is larger for new homes, while the relative change is larger for heat-pump conversions.

Moving to the other coefficients, new homes are much more likely to adopt heat pumps in the South and somewhat more likely to adopt heat pumps in rural areas. These results contrast with those above for heat-pump conversions, which are more geographically diffuse. New homes in the South, meanwhile, are much less likely to adopt natural gas and propane, while new homes in rural areas are less likely to adopt natural gas but more likely to adopt propane (presumaby in the Midwest). Finally, while home ownership is not predictive of heat pumps, new owner-occupied homes are much more likely to have natural gas and much less likely to have other forms of electricity.

4.3 Difference-in-differences style estimates

The price estimates above potentially suffer from omitted variables bias. To address this concern, we leverage variation in the timing of recent heat pump installations and changes in state-level energy prices to estimate a difference-in-difference style regression. To illustrate this approach, consider the following regression model:

$$y_i = \beta_0 + \beta_1 I(\text{Age} < 2)_i + \beta_2 I(\text{Age} < 5)_i + \beta_3 I(\text{Age} < 10)_i + \epsilon_i, \tag{7}$$

where note that the age range dummies are now nested: the $I(\text{Age} < 2)$ dummy is nested within $I(\text{Age} < 5)$ which is nested within $I(\text{Age} < 10)$. Thus, the coefficient β_1 for heat equipment less than 2 years old measures an acceleration (or deceleration, if negative) in the rate of heat pump conversion for homes that most recently replaced their heating equipment (within 2 years) relative to homes that replaced their equipment slightly less recently (3-4 years).

We estimate this model separately for every state to yield the state-specific change in the rate of heat

[13] Nearly 90% of respondents living in homes built in 2010 or later report that their heating equipment is less than 10 years old.

Table 5: *Regression results: heating technology choices in new homes*

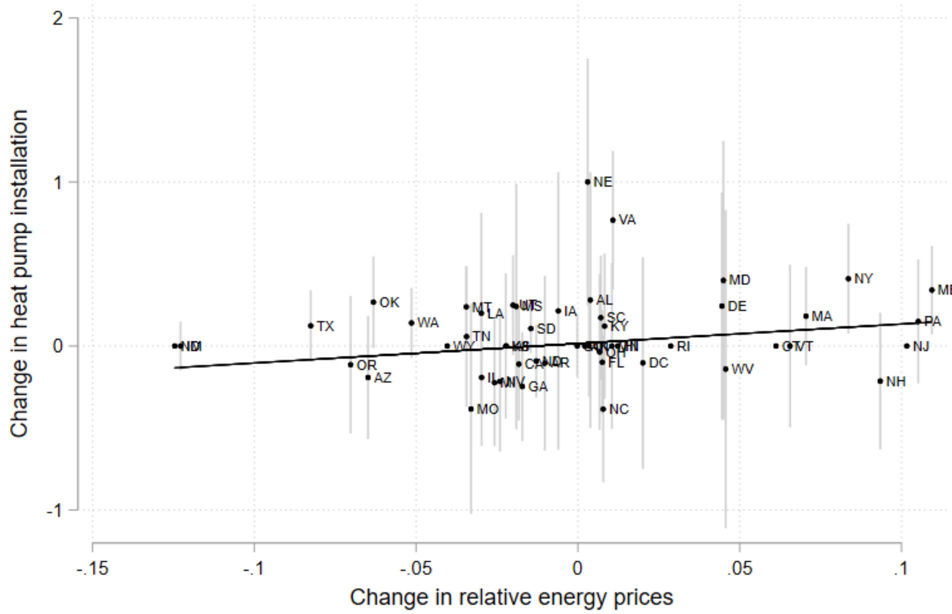
	(1) Heat pump	(2) Electric	(3) Natural gas	(4) Heating oil	(5) Propane
ln(pself)	-0.064	-0.349***	-0.406***	-0.001	0.001
	(0.089)	(0.092)	(0.065)	(0.000)	(0.003)
ln(pother)	0.231***	0.036	0.050	0.010*	-0.018
	(0.069)	(0.058)	(0.045)	(0.004)	(0.022)
\$30-39k	-0.005	-0.193**	0.147*	0.008	0.030
	(0.058)	(0.059)	(0.060)	(0.010)	(0.029)
\$40-49k	-0.038	-0.107	0.125*	-0.002	0.006
	(0.058)	(0.064)	(0.061)	(0.003)	(0.026)
\$50-59k	-0.016	-0.053	0.061	0.000	0.016
	(0.059)	(0.061)	(0.051)	(0.004)	(0.024)
\$60-74k	-0.102*	-0.037	0.149**	-0.003	-0.010
	(0.049)	(0.058)	(0.051)	(0.002)	(0.017)
\$75-99k	-0.025	-0.048	0.086*	0.004	-0.015
	(0.047)	(0.052)	(0.042)	(0.005)	(0.016)
\$100-149k	-0.041	-0.022	0.084*	-0.005*	-0.007
	(0.044)	(0.051)	(0.043)	(0.002)	(0.017)
\$150k+	-0.028	-0.136**	0.219***	-0.007*	-0.035*
	(0.044)	(0.048)	(0.042)	(0.003)	(0.015)
Midwest	0.063	-0.065	-0.039	-0.018	-0.069*
	(0.047)	(0.056)	(0.051)	(0.010)	(0.030)
South	0.191***	0.035	-0.179***	-0.027*	-0.132***
	(0.049)	(0.053)	(0.040)	(0.011)	(0.024)
West	0.068	0.042	-0.025	-0.023*	-0.128***
	(0.049)	(0.058)	(0.051)	(0.010)	(0.026)
Rural	0.057*	0.020	-0.207***	0.000	0.094***
	(0.027)	(0.028)	(0.026)	(0.003)	(0.015)
Owner	0.006	-0.260***	0.222***	0.005	0.023*
	(0.029)	(0.032)	(0.029)	(0.004)	(0.010)

Note: This table presents coefficient estimates from equation (6). The sample is homes built in 2010 or later. The dependent variable is an indicator for a given heating technology. Each column corresponds to a different technology. The table only reports coefficients on the interactions between the $I(\text{Age}0-4)$ dummy variable and the variables indicated in the table; main effects are not reported here. Observations are weighted by RECS sampling weights. Standard errors in parentheses are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: RECS 2020.

pump conversions in recent years. Figure 8 plots the resulting coefficient estimates vs. the change in relative energy prices in each state from 2016–2017 (3–4 years before 2020) and 2018–2019 (1–2 years before 2020).[14] The black dots represent the state-by-state point estimates, while the vertical bars represent the

[14]Relative energy price is defined as the weighted average of logged energy prices for technologies other than a heat pump minus the logged energy price for a heat pump. Recall that we measure energy prices in dollars per MMBTU accounting for

Figure 8: *Change in heat pump conversions vs. change in relative energy prices by state*



Note: This figure plots the estimated coefficient on the $I(\text{Age} < 2)$ dummy estimated separately for each state vs. the change in relative energy prices in that state. We measure relative energy prices in each state as: $\ln p_r = \sum_{j \neq hp} \theta_j \ln p_j / \sum_{j \neq np} \theta_j - \ln(p_{hp})$, where p_j is the mean per-MMBTU price of energy for heating technology j in a state and θ_j is the corresponding share of the state's households that report using that technology in RECS waves 2009 and 2015. That is, we measure relative energy prices as the weighted average of log energy prices for alternative technologies minus the log energy price for a heat. See section XXX for how we calculate technology-specific energy prices. We compute the per-MMTBU means separately for the 2016–2017 and 2018–2019 time periods. We then compute relative energy prices for each time period. Finally, we calculate the difference between the two time periods in each state to get the change in relative energy prices.

corresponding 95% confidence intervals. The figure also shows an OLS fitted line through the point estimates, with the point estimates weighted by households in the 2020 RECS sample. The figure shows that a recent increases in relative energy prices (i.e., alternative technologies relative to heat pumps) are associated with an acceleration in the rate of heat pump conversions in a given state.

To implement this approach statistically, we estimate a linear probability model of the form:

$$hp_i = \beta_0 + \beta_1 I(\text{Age} < 2)_i + \beta_2 I(\text{Age} < 5)_i + \delta I(\text{Age} < 2)_i \cdot \Delta pr0_i + \gamma \Delta \ln pr0_i + \epsilon_i, \tag{8}$$

where note that we have included the change in relative energy prices from from 2016–2017 to 2018–2019 (denoted by $\Delta \ln(pr0)$) plus its interaction with the $I(\text{Age} < 2)$ dummy. Our coefficient of interest is δ, which measures the extent to which an increases in relative energy prices over the last several years accelerates the

differences in the conversion of raw energy into usable heat. Weights are based on state-level fuel technology shares in the 2009 and 2015 RECS. We take logs first and then calculate the weighted average price for each state.

Table 6: *Regression results: heat-pump conversions in old homes*

	(1)	(2)	(3)	(4)
Age < 2	0.027	0.028	0.026	0.020
	(0.020)	(0.019)	(0.019)	(0.018)
Age < 5	0.005	-0.002	-0.003	-0.003
	(0.012)	(0.013)	(0.012)	(0.012)
Age < 10	0.075***	0.065***	0.066***	0.069***
	(0.014)	(0.012)	(0.012)	(0.012)
Age $< 2 \times \Delta \ln(ph0)$		-0.406		
		(0.305)		
Age $< 2 \times \Delta \ln(pb0)$		0.340		
		(0.251)		
Age $< 2 \times \Delta \ln(pr0)$			0.307	0.305
			(0.222)	(0.220)
$\Delta \ln(ph0)$		-0.531		
		(0.544)		
$\Delta \ln(ph1)$		-1.031*		
		(0.471)		
$\Delta \ln(pb0)$		0.276		
		(0.523)		
$\Delta \ln(pb1)$		0.768		
		(0.394)		
$\Delta \ln(pr0)$			0.423	0.562
			(0.456)	(0.420)
$\Delta \ln(pr1)$			0.869**	0.836**
			(0.305)	(0.277)

Note: This table presents coefficient estimates from equation (7). The sample is homes built in 2009 or earlier. The dependent variable is an indicator for air-source heat pump. Observations are weighted by RECS sampling weights. Standard errors in parentheses are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: RECS 2020.

rate of heat pump conversions. Note that we also include the $I(\text{Age} < 10)$ dummy and changes in relative energy price from 2010–2015 to 2016–2017 (denoted by $\Delta \ln(pr1)$) as controls in our regression.

Table 6 presents our OLS estimation results. Column (1) regresses the heat pump indicator on the nested age dummies without any interactions. The coefficient on $I(\text{Age} < 2)$ indicates that conversion shares have accelerated by 0.027 in the last couple years (equipment age 0–2 years) relative to the couple years before that (equipment age 3–4 years). Column (2) interacts the $I(\text{Age} < 2)$ dummy with energy prices, separating the change in energy price for heat pumps (denoted by $\Delta \ln ph0$) from the change in energy price for alternative technologies (denoted by $\Delta \ln pb0$).[15] Here we see that a 10% increase in energy price for heat pumps is associated with a 0.041 deceleration in the conversion share, while a 10% increase in energy price for alternative technologies is associated with a 0.034 acceleration in the conversion share. Column (3) imposes the restriction that these coefficients are identical in magnitude. Here we see that a 10% increase in relative energy price is associated with a 0.031 acceleration in conversion share. The coefficient is marginally significant with a one-sided P-value of 0.083. Column (4) controls for categories of household income, renter vs. owner-occupied, urban vs. rural, and home vintage. The coefficient on the interaction between equipment age and energy price barely budges.

For comparison, we perform a similar exercise for new homes built in 2010 or later. As above, we regress the heat pump indicator on a set of nested age dummies, interpreting the coefficient on $I(\text{Age} < 2)$ as the change in the share of heat pumps for new homes built within the last couple years relative to homes built slightly earlier. We first estimate this regression separately for every state and plot the resulting coefficients relative to the change in relative energy prices. We find that increases in relative energy prices are associated with an increased rate of heat pump adoption in new homes, and that this association is stronger than heat pump conversions in older homes (see figure 14 in the appendix).

We then interact the $I(\text{Age} < 2)$ dummy with changes in relative energy prices over the past couple of years, to test whether higher energy prices lead to increased adoption of heat pumps in new homes. Table 7 presents our OLS estimation results. Column (1) regresses the heat pump indicator on the nested age dummies. The coefficient on $I(\text{Age} < 2)$ indicates that heat pump adoption among new homes has accelerated by 0.049 in the last couple years. Column (2) interacts the $I(\text{Age} < 2)$ dummy with energy prices for heat pumps and alternative technologies separately. The results are noisy. Column (3) imposes the restriction that these coefficients are identical in magnitude. Here we see that a 10% increase in relative energy price is associated with a 0.086 in heat pump adoption among new homes, which is a substantially stronger effect than conversions in old homes. Again, the coefficient is marginally significant with a one-sided P-value of 0.086. Column (4) controls for categories of household income, renter vs. owner-occupied, urban vs. and rural (but not vintage, since the houses are all new) and finds similar results.

4.4 Summary of findings for heat pump conversions

Overall, we estimate a 6%–8% increase in the share of existing homes that use heat pumps as their main heating technology over the past decade due to conversions. We estimate that these conversions account for at least 75% of all heat pump installations over the last decade. While 25% of new homes built in the last

[15] The "h" in $\ln(ph)$ indicates heat pump while the "b" in $\ln(pb)$ indicates base technology. The "r" in $\ln(pr)$ indicates the difference: $\ln(pr) \equiv \ln(pb) - \ln(ph)$. Meanwhile, the Δ's indicate changes over time. Finally, the 0's and 1's indicate timing. The 0's correspond to the most recent price changes (2019–2018 minus 2016–2017) while the 1's correspond to changes lagged one time step (2016–2017 minus 2010–2015.

Table 7: *Regression results: heat-pump choices in new homes*

	(1)	(2)	(3)	(4)
Age < 2	0.049	0.046	0.061	0.054
	(0.039)	(0.042)	(0.043)	(0.044)
Age < 5	-0.009	-0.004	-0.004	-0.005
	(0.042)	(0.040)	(0.040)	(0.040)
Age < 10	0.057	0.053	0.052	0.050
	(0.035)	(0.034)	(0.035)	(0.034)
Age $< 2 \times \Delta \ln(ph0)$		-0.078		
		(1.026)		
Age $< 2 \times \Delta \ln(pb0)$		0.932		
		(0.583)		
Age $< 2 \times \Delta \ln(pr0)$			0.855	0.739
			(0.626)	(0.609)
$\Delta \ln(ph0)$		-1.776*		
		(0.828)		
$\Delta \ln(ph1)$		-1.104**		
		(0.329)		
$\Delta \ln(pb0)$		1.039*		
		(0.467)		
$\Delta \ln(pb1)$		1.192***		
		(0.325)		
$\Delta \ln(pr0)$			1.054*	1.089*
			(0.451)	(0.437)
$\Delta \ln(pr1)$			1.126***	1.129***
			(0.189)	(0.186)

Note: This table presents coefficient estimates from equation (7) but applied to new homes. The sample is homes built in 2010 or later. The dependent variable is an indicator for air-source heat pump. Observations are weighted by RECS sampling weights. Standard errors in parentheses are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: RECS 2020.

decade rely on heat pumps, such homes account for just 8% of the housing stock in 2020.

These conversions have occurred in every region, among both urban and rural households, and among every income group. We infer that these conversions are mainly replacing natural gas, heating oil, and electricity, depending on which of these fuels is most prevalent locally.

Finally, we find evidence that these conversions are quite responsive to the price of electricity relative to natural gas, heating oil, and propane. In absolute terms, technology choices are more responsive to energy prices in new homes. But relative to baseline levels of adoption, conversions in old homes are equally or even more price-sensitive.

5 Private benefits of electrification via heat pumps

To explore the distributional implications of heat pump adoption, we assemble a spatial data set at the U.S. census tract level and calculate the approximate annual energy-cost savings from adopting a heat pump for a prototypical home in each census tract. For accuracy, we incorporate utility-level electricity prices and state-level propane, fuel oil, and natural gas prices, and we estimate fuel-agnostic expected energy consumption for home heating using EIA RECS data from 2009 and 2015. We then use tract-level data on current heating fuel shares to calculate a tract-level composite cost of heating. Finally, we compare this composite cost of heating to the annual cost of serving the same level of energy consumption (in MMBTU) with a heat pump.

We estimate annual consumption for heating purposes in MMBTU for household i as a flexible function of HDD_i, home vintage, and total square footage (sqft). We use a 5th degree polynomial in HDD_i and fit the following regression to RECS data from 2009 and 2015:

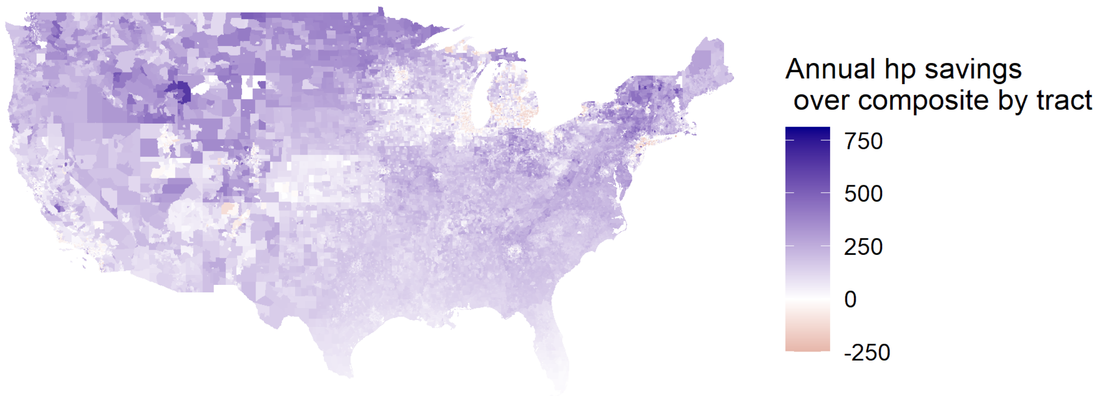
$$MMBTU_i = \beta_0 + \sum_{p=1}^{5} \beta_p HDD_i^p + \beta_6 sqft + \mathbf{\Gamma}_1 YearBuilt_i + \mathbf{\Gamma}_2 \left(YearBuilt_i \times sqft_i\right) + \varepsilon_i, \qquad (9)$$

where HDD_i is the RECS-reported heating degree days using a base temperature of 65 degrees Fahrenheit. We exclude all households that report using a heat pump for a primary heating technology so that estimates of β are targeted at predicting non-heat pump household energy consumption in MMBTU. Finally, we predict $MMBTU_r$ for each census tract assuming a 1500 square foot home constructed between 1960 and 1969 and using the 30-year county-level average HDD measure reported by NOAA's National Center for Environmental Information for 2018.[16]

The energy-cost savings from adopting a heat pump depends on the current fuel used by a household. Within a census tract, a variety of fuels may be employed by individual households. Thus, we report savings conditional on fuel type (natural gas, propane, fuel oil, and resistance electricity) in the appendix, and we construct a weighted average of savings using reported fuel type from the U.S. Census American Community Survey 5-year estimates for 2018. We calculate annual savings conditional on fuel type as the difference in annual costs for serving the predicted MMBTU using a given fuel type vs. using a heat pump. We use inflation-adjusted average variable cost per kilowatt-hour (kwh) at the utility level for the period 2014–2018. For utilities that do not report to EIA-861, we assign the state average calculated over all non-reporting utilities ("state adjustment" in EIA parlance). For natural gas, we use state-average prices per thousand

[16]Here: https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/mapping/110-hdd-201804-24.csv

Figure 9: *Annual savings from heat pump adoption by census tract*



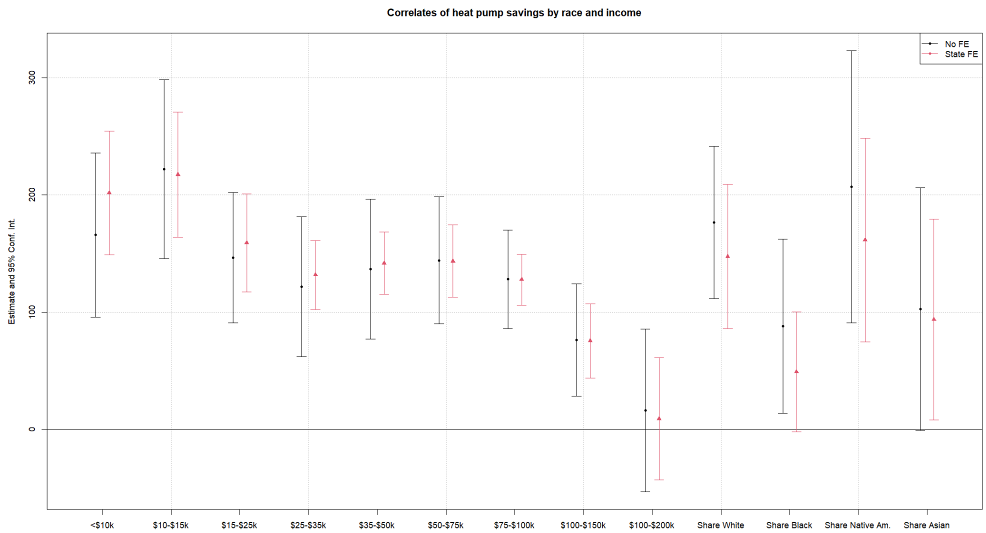
Note: This figure calculates the annual heating cost savings attributed to adoption of a heat pump. It incorporates local electricity costs, state-level natural gas, fuel oil, and propane prices, and weights the incumbent technology by each tract's fuel share. Calculations are based on a 1,500 square foot home built between 1960 and 1969. The figure represents the expected savings for a randomly chosen household from the tract. The extreme negative outlier is Block Island, RI, which has the highest electricity price in the lower 48 states, and is the site of the United States' only offshore wind farm.

cubic feet (MCF).[17] For fuel oil and propane, use use state-average prices per gallon from EIA. The EIA does not report propane and heating oil prices for all states (e.g., fuel oil prices in California). In such cases, we assign the U.S. average price. These states tend to have very few users of propane and heating oil. Thus, we do not expect substantial biases to arise due to lack of state-specific price data for these fuels. As described above in section 2, we convert all energy prices to dollars per MMBTU of usable heat, accounting for the BTU content of each fuel, as well as the efficiency factors of different heating technologies. Finally, we calculate the annual cost of heating using the composite fuel in each census tract minus the cost of heating with a heat pump (assuming a fixed MMBTU of heating demand that varies by census tract).

Figure 9 displays the results of this calculation geographically for each census tract. Results show that the vast majority of tracts would realize annual energy-cost savings from adopting a heat pump. Some areas centered around Detroit, Michigan and Southern California would see energy-cost increases, indicating the

[17] We plan to use utility-level prices rather than state-level prices in future iterations of this paper.

Figure 10: *Correlates of annual energy-cost savings from heat pump adoption by census tract*



Note: This figure shows the correlates between share of households in each income bin and race and the expected savings from switching from the composite incumbent fuel type to a heat pump. The base levels are $> \$200k$ and "other/more than one race". Positive signs indicate a *higher* expected savings when the share of households in the tract that fall in each bin increases.

current (dominant) fuels are less expensive per MMBTU than electricity (after accounting for a heat pump's efficiency gain). Tracts exhibiting the largest savings from heat pump adoption are located near the Rockies and the upper plains, as well as in northern New England. These areas have colder winters and larger numbers of heating degree days. Due to the low daily minimum temperatures, cold-weather heat pumps are necessary to ensure suitable heating during the coldest periods. Outside of these extremely cold areas, the tracts with the largest savings are located in the upper mid-Atlantic and along the Pacific coast.

To explore the distributional implications of heat-pump adoption, we estimate the following equation:

$$CompositeSavings_r = \beta_0 + \sum_{d \neq \$200k+} \beta_d ShareIncome_r^d + \sum_{e \neq other} \beta_e ShareRace_r^e + \varepsilon_r, \tag{10}$$

where $ShareIncome_r^d$ is the share of households in tract r whose income lies within income bin d, and $ShareRace_r^e$ is the share of people in tract r that are of race e.

Figure 10 shows results from this estimation. For all but the second-highest income bins, the expected energy-cost savings (again, assuming a 1500 square-foot home built in 1960–1969) are *greater* than the expected savings for the highest income bin. Home size is held constant by assumption. Thus, the correlation is across tracts for houses of the same size. Census tracts with lower electricity prices, higher shares of households using expensive heating options (e.g. fuel oil), and more heating degree days per year tend to be tracts with larger shares of low- and medium-income households. The relationship maintains when adding state fixed effects. Additionally, results for race show that heat pump savings are positively correlated with share White and share Native American, relative to a base of “other/more than one race.” This is consistent with rural areas served by propane and heating oil displaying the largest heat pump savings.

5.1 Heat pump market shares

In colder areas with access to natural gas, Figure 9 shows lower overall heat pump savings. In this section, we examine data on heat pump shipments obtained from HARDI, described above, to test for a similar relationship in observed heat pump shipments. If consumers are responsive to the relative fuel prices driving the variation in heat pump savings, we should observe (i) declining heat pump market shares when natural gas availability increases, and (ii) lower heat pump market shares when population density increases.

Figure 15 shows the relationship between heat pump market shares at the zip code level and the fraction of population in the zip code that have natural gas hookups. The availability of gas exhibits a strong negative correlation with the market share of heat pumps, consistent with the heat pump savings results. The relationship between heat pump market share and population density is not as strong (see Figure 16) but exhibits a clear downward trend – heat pump market share decreases as population density increases.

6 Conclusion

We study heat-pump conversions in the United States over the last decade. We estimate a 0.06–0.08 increase in the share of existing homes with heat pumps during 2009–2020. Our results imply that conversions account for three-quarters of the heat pumps adopted during this period. We show that these conversions are widespread, occurring throughout the income distribution, in both urban and rural areas, and in every region of the country. Based on our current methods, we are only able to identify net conversions. Thus, future iterations of this paper will study transitions from one heating technology to another using micro panel data from the American Housing Survey for 2015–2021.

Our empirical analysis shows that heat pump conversions are sensitive to energy prices, as are installations in new homes. Our current approach compares technology choices in states with low vs. high prices for electricity relative to other fuels. Yet the incentive to install a heat pump in theory should depend on the overall cost of heating, which scales with energy prices, cold temperatures, and home size. Thus, future iterations of this paper will include a refined empirical analysis that captures variation in heating costs driven by HDD and home size, in addition to energy prices.

Finally, our calculations reveal large geographic dispersion in the private energy-cost savings from adopting a heat pump, driven by local energy prices and climate conditions. Cross-sectional correlations by census tract suggest that heat-pump adoption would disproportionately benefit low-income households living in rural areas, who tend to rely on propane, heating oil, and electric-resistance heating. Our current analysis takes electricity and natural gas prices as given. Yet it is becoming increasingly clear that variable prices deviate substantially from private costs in many utility areas, due to inefficient two-part tariffs and steeply increasing block-rate schedules (Borenstein and Bushnell 2018). Thus, future iterations of this paper will consider distributional implications under the counterfactual assumption of efficient two-part tariffs.

A Tables

Table 8: *Share of old homes with different heating technologies*

	(1) HP	(2) Elec	(3) Gas	(4) Oil	(5) Prop
RECS 2009	0.089***	0.259***	0.508***	0.068***	0.051***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)
RECS 2015	0.103***	0.255***	0.515***	0.053***	0.044***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.002)
RECS 2020	0.153***	0.250***	0.489***	0.046***	0.043***
	(0.003)	(0.004)	(0.005)	(0.002)	(0.002)
Observations	49584	49584	49584	49584	49584

Note: This table presents coefficient estimates from XXX. Standard errors are robust to heteroskedasticity. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively.
Data source: RECS 2009, 2015, and 2020.

Table 9: *Regression results: heating technology conversions in old homes*

	(1) Heat pump	(2) Electric	(3) Natural gas	(4) Heating oil	(5) Propane
0-4 yrs	0.092***	0.021*	-0.083***	-0.031***	0.006
	(0.008)	(0.010)	(0.011)	(0.004)	(0.004)
5-9 yrs	0.075***	-0.008	-0.040***	-0.022***	-0.002
	(0.009)	(0.010)	(0.012)	(0.004)	(0.004)

Note: This table presents coefficient estimates from a regression of heating technology indicators on equipment age dummies in the 2020 RECS. Standard errors in parentheses are clustered by state. Note *, **, and *** indicate statistical significance at the 5%, 1%, and 0.1% levels respectively. Data source: 2020 RECS.

B Figures

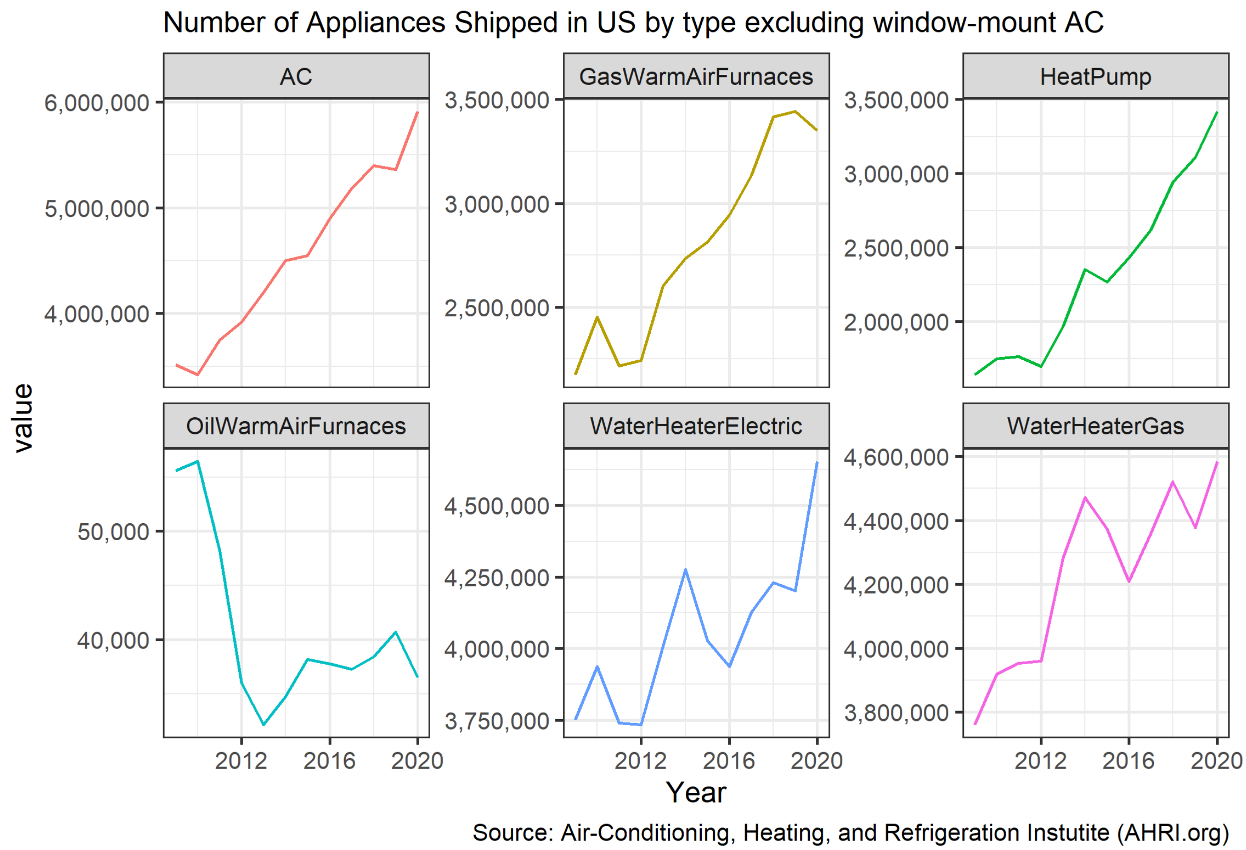


Figure 11: *Number of appliances shipped in the United States by technology 2009–2020*

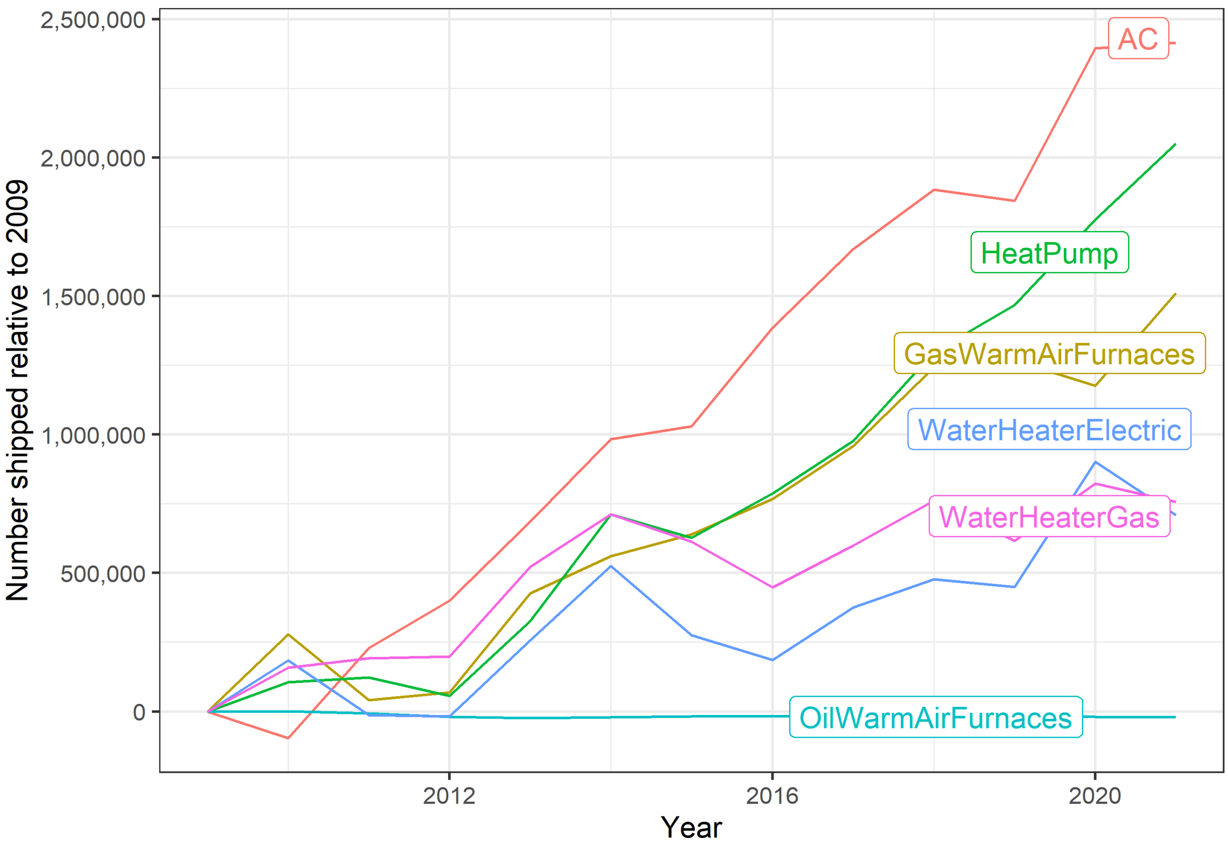


Figure 12: *Number of appliances shipped in the United States by technology indexed to 2009*

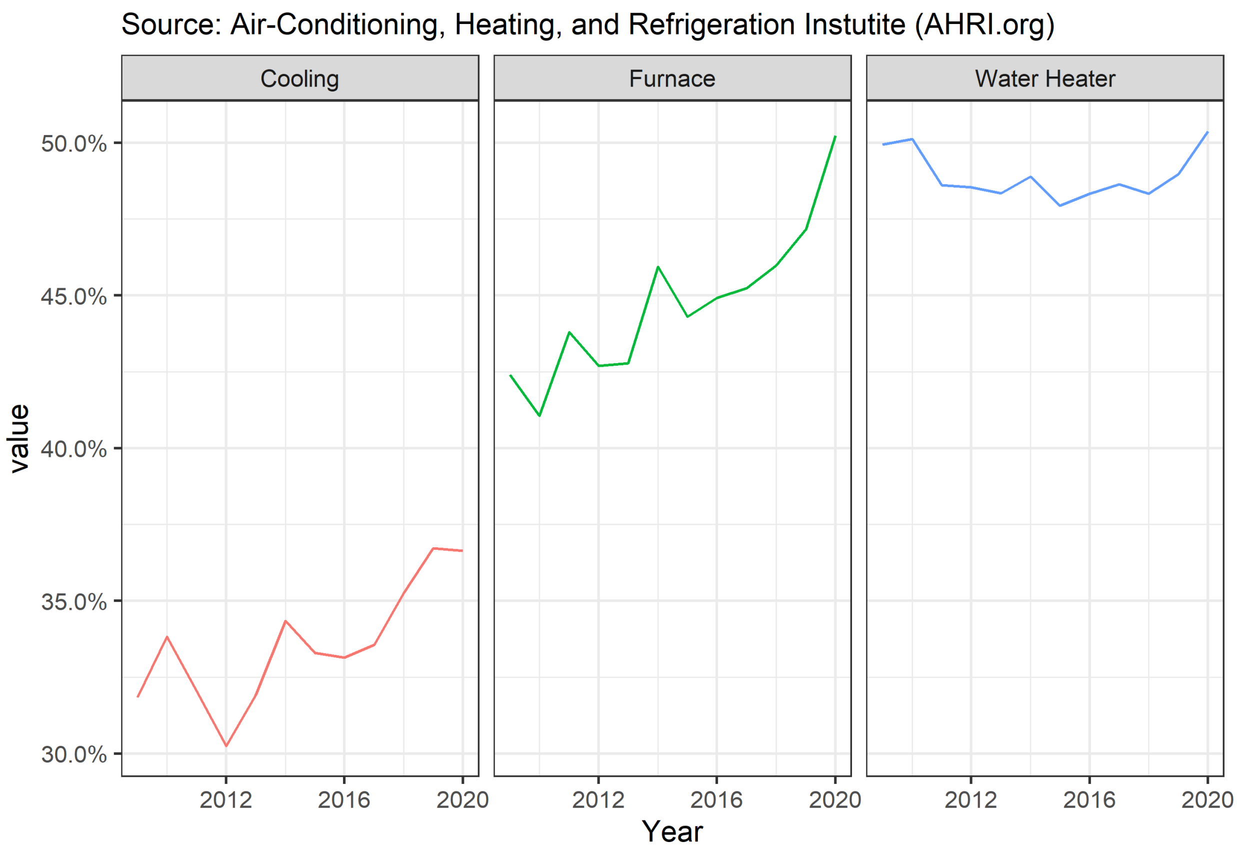
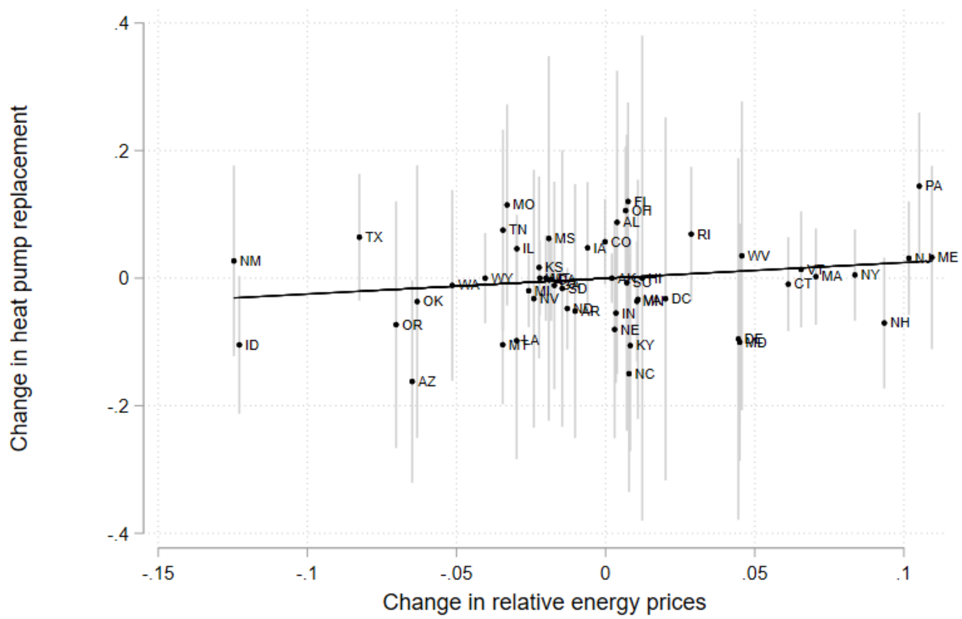


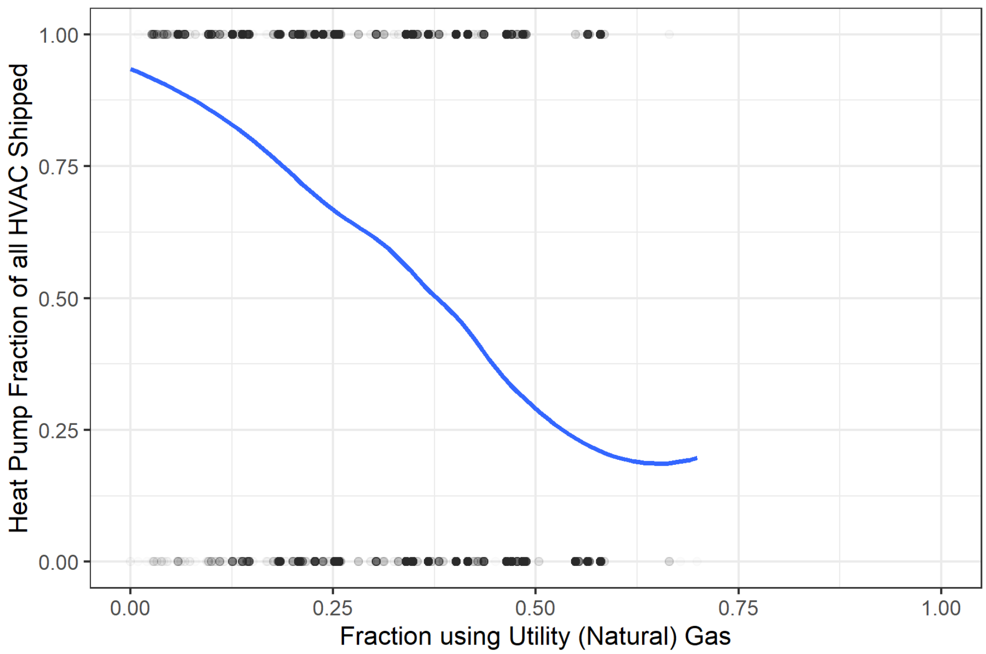
Figure 13: *Heat pump share of HVAC appliances shipped in the United States 2009-2020. Left panel indicates the fraction of air conditioning units that used heat pump technology (heating and cooling) relative to all air conditioning units (excluding window units). Center panel indicates the fraction of all heating units (gas, oil, and electric) that used heat pump technology. Right panel indicates fraction of all hot water heaters using electricity (heat pump and resistance).*

Figure 14: *Change in heat pump installations vs. change in relative energy prices by state: new and old homes*



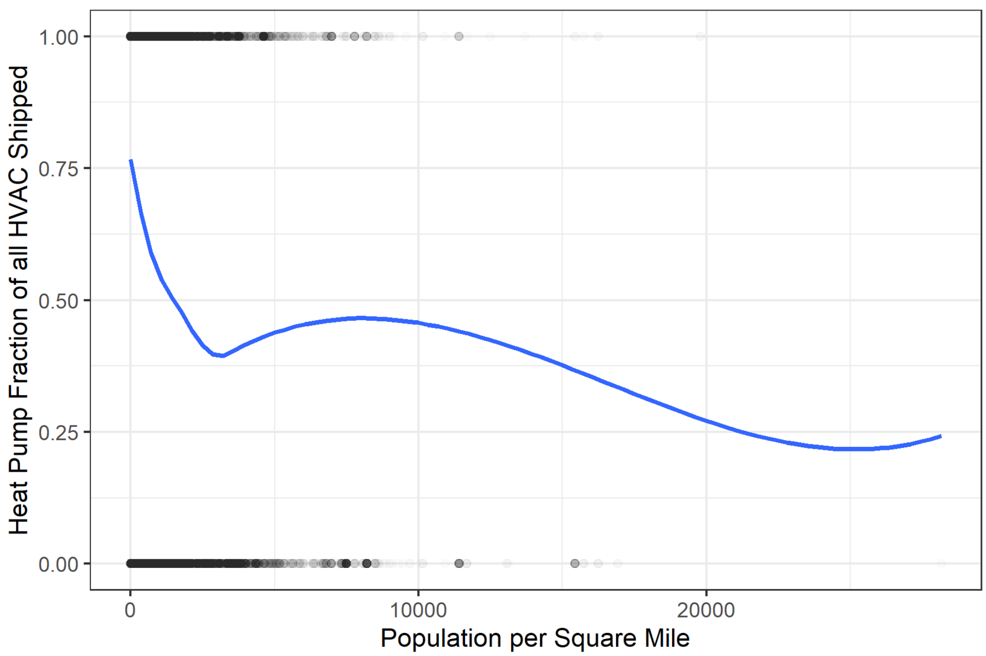
Note: This figure plots the estimated coefficient on the $I(\text{Age} < 2)$ dummy for each state vs. the change in relative energy prices in that state. We measure relative energy prices in each state as: $\ln p_r = \sum_{j \neq hp} \theta_j \ln p_j / \sum_{j \neq np} \theta_j - \ln(p_{hp})$, where p_j is the mean per-MMBTU price of energy for heating technology j in a state and θ_j is the corresponding share of the state's households that report using that technology in RECS waves 2009 and 2015. That is, we measure relative energy prices as the weighted average of log energy prices for alternative technologies minus the log energy price for a heat. See section XXX for how we calculate technology-specific energy prices. We compute the per-MMTBU means separately for the 2016–2017 and 2018–2019 time periods. We then compute relative energy prices for each time period. Finally, we calculate the difference between the two time periods in each state to get the change in relative energy prices.

Figure 15: *Heat pump market share by natural gas availability*



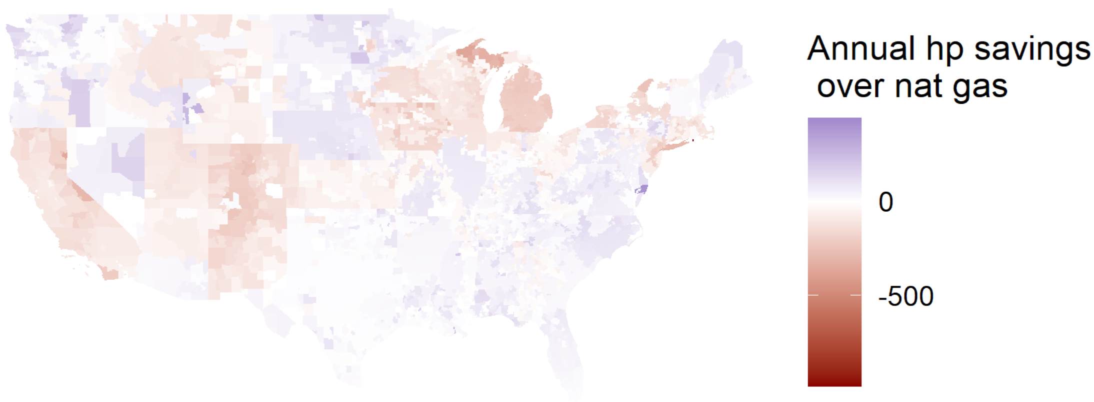
Note: This figure calculates a loess smoothed relationship between the fraction of households in a market that have natural gas hookups and heat pump market share. The decreasing relationship implies that markets with higher access to natural gas hookups have lower market shares of heat pumps. Sample is only western and southern states. Source: Author calculations from HARDI proprietary data.

Figure 16: *Heat pump market share by population density*



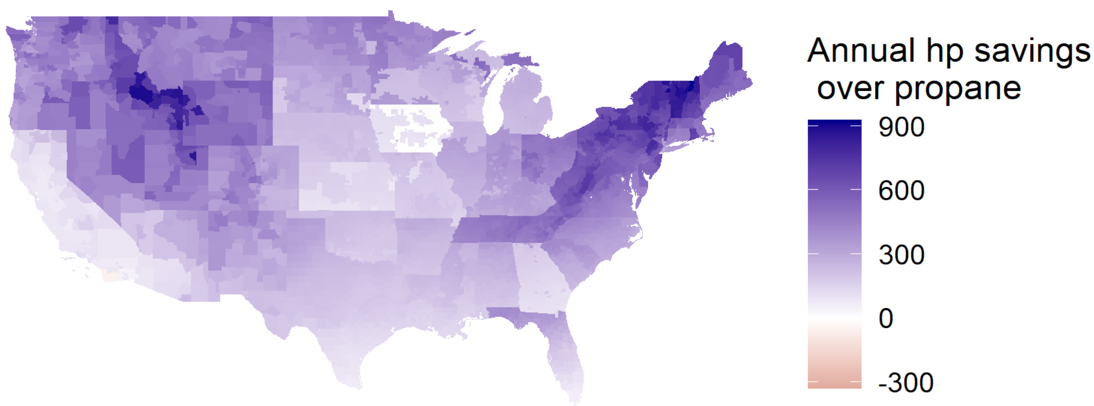
Note: This figure calculates a loess smoothed relationship between the population density and heat pump market share. Each point represents a market, where the market is defined by the intersection of electric utility, gas utility, and state. The decreasing relationship implies that markets with higher population density have lower market shares of heat pumps. Sample is only western and southern states shown in 2. Source: Author calculations from HARDI proprietary data.

Figure 17: *Annual savings from switching from natural gas to heat pump*



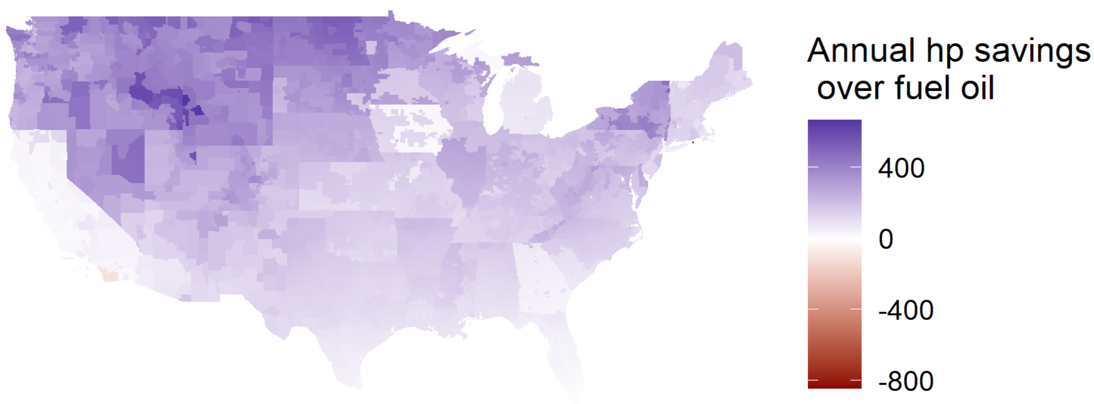
Note: This figure calculates the savings from switching from piped natural gas to a heat pump based on the tract's price of electricity and natural gas, and the expected consumption in MMBTU for space heating a 1,500 square foot home build in the 1970's.

Figure 18: *Annual savings from switching from propane to heat pump*



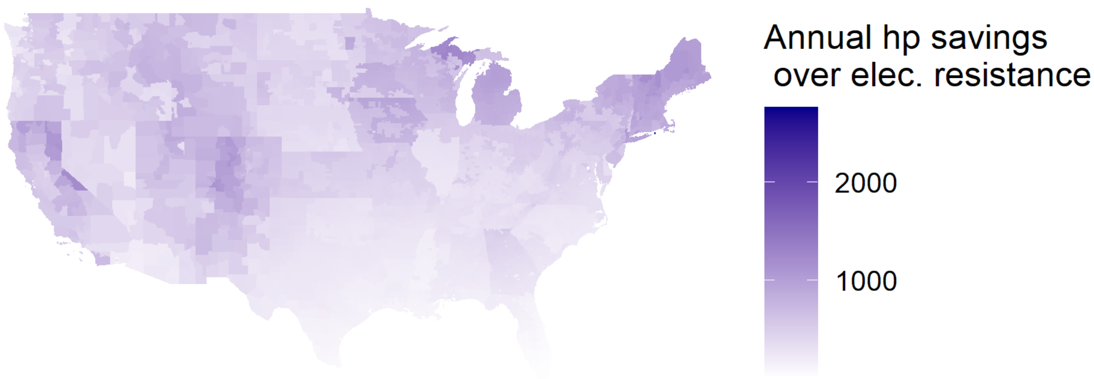
Note: This figure calculates the savings from switching from propane to a heat pump based on the tract's price of electricity and propane, and the expected consumption in MMBTU for space heating a 1,500 square foot home built in the 1970's.

Figure 19: *Annual savings from switching from heating oil to heat pump*



Note: This figure calculates the savings from switching from heating oil to a heat pump based on the tract's price of electricity and heating oil, and the expected consumption in MMBTU for space heating a 1,500 square foot home built in the 1970's.

Figure 20: *Annual savings from switching from electric resistance to heat pump*



Note: This figure calculates the savings from switching from electric resistance to a heat pump based on the tract's price of electricity, and the expected consumption in MMBTU for space heating a 1,500 square foot home built in the 1970's. Heat pumps are 300% efficient relative to resistance. As a result, all tracts see significant savings. Savings are purely a function of electricity prices.

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