Contractor Learning and Home Energy Efficiency in Heat Pump Installations

by

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ABSTRACT

The displacement of fossil-fuel based heating is essential for achieving decarbonization in the building sector, which represents about a third of national emissions in the United States. Electric heat pumps are the primary technology needed to do so, but widespread adoption is hindered by a variety of factors including higher upfront costs and a shortage of experienced labor to fulfill installations. This work examines the role of learning on the cost and size of heat pump installations throughout the Massachusetts Clean Energy Center (MassCEC) rebate program. We find that as contractors gain experience, heating systems are downsized at the cost of less hours of displaced fossil-fuel based heating. This learning impact is strongest for homes with a natural gas backup heater, which is the cheapest source of heating in Massachusetts followed by electric heat pump heating. We then analyze the structure of the MassCEC rebate, and its potential influence on the benefits of the program.

Thesis supervisor: Siqi Zheng
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Contents

List of Figures

List of Tables

Chapter 1

Introduction

In 2020 the use of fossil fuels for combustion in residential and commercial buildings represented 7 and 5 percent of total CO2 emissions in the United States [1]. These emissions are largely due to on-site burning of natural gas and oil for heating, with natural gas alone representing 81% of *direct* fossil fuel CO2 emissions [1]. Buildings as a whole represent a a third of national emissions [1], and the replacement of existing heating systems is a key barrier to meeting net-zero goals by 2050 [2].

High-efficiency electric heat pumps, which provide the most energy-efficient solution to space heating and cooling, are considered the most promising solution to reduce emissions from the building sector [3]. According to the International Energy Agency (IEA), the number of heat pumps must increase globally from 180 million (2020) to 600 million installed units by 2030 to support the net-zero targets pledged by major economies, tripling the existing space heated by this technology [4]. In the United States the remaining gap for 2030 goals is 15 million installations from 5 million as 2020 [5].

There are however several barriers to widespread adoption of heat pumps such as higher upfront costs of installation compared to the replacement of existing natural gas and oil furnaces and the lack of qualified and experienced contracting companies [4]. Furthermore, a heat pumps reliance on an effective building envelope poses a challenge for older housing stock that must upgrade its poor insulation for a heat pump to work efficiently [2]. Finally, for non single-family-owned homes, the incentives to adopt a heat pump are mixed between tenant energy savings, the building-owner's upfront costs, and the disruption needed to complete an installation.

In this thesis I focus on the challenge of experienced installers by examining the effects of learning on contractor installation behavior using data from the Massachusetts Clean Energy Center (MassCEC) heat pump rebate program, followed by an analysis on the trade-offs in fuel cost and emissions generated by shifting heating methods. The remainder of the introductory chapter gives background to the heat pump installation process and the data used. The analyses are split across three chapters:

1. The examination of individual contractor behavior and the "learning effect".
2. The development of residential building energy models to evaluate the sizing of installations.
3. An analysis of the MassCEC rebate structure and the role of "learning by doing".

Finally, this thesis is closed off with a discussion across all three sections. The primary contributions of this work advancing of the learning by doing literature to heat pump technology, along with the novel combination of real heat pump installation data with the current state-of-the-art building energy simulation tools to evaluate installations in a way that was previously impossible.

1.1 Heat pumps and the pathway to decarbonizing the residential sector

Meeting net-zero goals by 2050 requires large reductions in emissions from our buildings, which can be achieved through various means like improved energy efficiency through retrofitting of existing buildings, or the replacement of older housing stock. In their seminal publication, Berrill and co-authors compare decarbonization outcomes across the evolution of housing stock and electricity generation scenarios [6]. Specifically, they examine the evolution of housing stock across three axes: **housing stock quantity and turnover:** the number of new units built and the persistence of existing buildings, **new housing characteristics:** the size and electrification rate of new homes, and **renovation of existing stock:** the depth of renovation implemented for the current existing stock. Berrill's analysis takes into consideration the trade-off between building new purpose-built homes that are better suited for heat pumps and the embodied emissions resulting from the materials and construction of the new stock. The large majority (>90%) of the installations in the MassCEC rebate data were *retrofitted* heat pump systems installed in existing homes, replacing a previous natural gas or oil furnace as the primary source of heat.

Though there is regional variability, the associated emissions with building new housing stock outweigh the gains in average energy efficiency, making the renovation of existing stock a more effective general strategy for the United States when combined with effective decarbonization of electricity supply: "ER [extensive renovation] has greatest influence in regions with cold/mixed climates, low GHG-intensity electricity, low shares of electric heating higher shares of old housing and lower population growth. New England (northeast United States) and New York state demonstrate the greatest potential, with 31–35% reduction of cumulative emissions" [6]. This means that the successful implementation of heat pump retrofits with the current stock is a winning strategy for decarbonization.

As a final note, Berrill points towards two important considerations on the use of heat pumps for the extensive renovation strategy, the first being that heat pumps work best with well insulated homes, which is reflected in their simulations indicating the highest reduction in GHG emissions from combination of envelope renovations and heat pump retrofits in cold climates [6]. The second is that heat pumps are most economical when replacing fuel oil and propane heating, but can be more expensive than natural gas heating [6]. The implications of cost differences between heat pumps and natural gas heating in terms of upfront equipment *and* fuel (operational) cost are explored throughout this work.

Furthermore, this private cost towards the homeowner of heat pump adoption comes at the societal benefit of reduced CO2 emissions from displaced fossil-fuel use. The tradeoff between the two brings the economic reasoning behind subsidy programs that promote adoption. Existing literature on the cost effectiveness of heat pumps point towards the cost of electricity, and magnitude of cold weather exposure as the primary drivers of private cost [7], [8]. Massachusetts, which is both a state with a cold climate and nationally high electricity rates[8], makes an interesting case study for heat pump uptake. The literature surrounding the social benefits of increased heat pump penetration is complex and developing. On the home-level, a heat pump displaces CO2 emissions by using electricity, but on a larger scale poses increased demand on the electric grid, making the exact magnitude of societal benefit ambiguous [9]. In the fourth chapter of this thesis, back-of-the-envelope calculations of emissions are taken primarily as a tool for understanding the broad implications of changes in heat pump adoption.

1.2 Required skillset and training for heat pump contractors

The deployment of a heat pump in residential properties is a demanding exercise that requires a highly skilled HVAC contractor to do a variety of tasks, some of which are novel to experienced contractors who have primarily worked with gas and oil-based heating in the past. First, the installation of a heat pump requires a more complex assessment of the right sizing than the evaluations commonly used for gas heaters, considering factors such as the quality of the building's insulation rather than solely the square footage of conditioned space [10], [11].

Additionally, the installation of heat pumps tends to require the upgrade of existing elements of the heating system and/or the electric system of the property. For this, installers need to assess the expected energy demand for the climate of the location. An improper assessment of the heating needs of the building can have a substantial impact on performance [10]. In a recent study done by the U.S. Department of Commerce, the faults with the most potential for performance degradation and increased annual energy consumption were duct leakages, refrigerant under or overcharge, oversized heat pumps, and low indoor airflow due to undersized ductworks [10]. A proper installation, therefore, requires a nuanced understanding of a building's heating needs, its current infrastructure compatibility, and good judgment on whether further modifications, such as the improvement of insulation or resizing of existing ductwork is needed.

The shortage of active training programs for contractors makes them rely on passive on-the-job strategies to learn how to select the right-sized heat pump for houses. There are limited certification requirements for HVAC contractors that install heat pumps. In Massachusetts, for instance, there are no required HVAC certifications for practice, with optional national certifications such as the North American Technician Excellence (NATE) certification.[1] These certifications do not overlap with the certifications required for fossil fuel-based heating: a license issued by The Board of State Examiners of Plumbers and Gas Fitters to Journeyman or Master plumbers for gas heaters, or a Oil Burners Technician Certificate for oil heaters [12], [13].

1.3 Learning by doing

"Learning by doing" (LBD) refers to the process by which a worker's performance increases over completing repeated tasks, and is often linked to the learning curve, which describes the rate of increased productivity as the worker gains experience. Early applications of LBD focused on its strategic implications in industrial settings, such as the decreasing amount of labor hours needed to produce an airframe as a manufacturer's plant gains experience [14]. In the past decade, applications of LBD have been made on renewable energy and efficiency technologies. A prime example of this is the study on LBD throughout the California Solar Initiative done by Bollinger and Gillingham [15]. Over a ten year period they estimate that non-harware costs of solar panel installations have fallen by 12 cents per watt due to LBD [15].

This finding is particularly relevant for heat pumps, where higher costs are a barrier to widespread adoption. Second, LBD can be used as a justification for the societal cost of rebate programs. An earlier study done by Gillingham weighs the cost of the environmental externalities mitigated from solar panel installations against the subsidy provided [16]. The primary finding is that the reduction in emissions from installing a solar panel are too small to justify California's subsidy, but with modest estimates on LBD effects decreasing cost over time, the subsidy amount is correctly priced [16]. By estimating the effects of learning

[1] In order to work with refrigerants, which are used in the installation and maintenance of heat pumps and air conditioners, Massachusetts adheres to the EPA section 608 Refrigerant Certification which is received upon scoring a passing grade on the section 608 examination **EPA-Section-608**.

in heat pump installations, this thesis seeks to draw similar insights about the economic efficiency of the MassCEC heat pump rebate program.

1.4 MassCEC rebate program

The Massachusetts Clean Energy Center ran a rebate program for qualifying cold-climate heat pump models from 2014 to 2019. There are two key aspects of the rebate structure:

1. The rebate is on a per-unit basis: after the base rebate for an installation, an additional \$750 or \$1,000 is given per heat pump unit installed, up to three units.. So long as the heat pump satisfies the base capacity requirement, the relevant characteristics like the range of heating capacity or rating of the heat pump do not change the rebate amount.

2. The rebate does not require a full replacement of the previous source of heating (i.e., a removal of gas heater).

Table 1.1: MassCEC Rebate Compensation Structure

Rebate Type	Single Head	Multi Head	Max Units
Base Rebate	$500	$500	3
High Income	$750	$750	3
Low Income	$1,000	$1,000	3

In the process of applying for the rebate, homeowners or the contractors who completed the installation detailed information about the home and heat pump system installed. The collected data forms the basis of this work.

1.5 Rebate and home characteristics data

MassCEC rebate data

As stated in the previous section, the MassCEC rebate data is the foundational source of information on heat pump installations. These data cover Massachusetts homes who installed a cold-climate heat pump system between the years 2014-2019. Each recorded row represents one home's installation, including key information such as the location of the

Table 1.2: Variables Available in MassCEC Rebate Data

Date of Installation	
Total Cost	The total recorded cost of installation, including equipment and labor.
Square Footage	The square footage of living area in the home.
County	The Massachusetts county in which the home is located.
Town	The town in which the home is located.
Past Fuel	The heating fuel source used by the home (i.e. gas or oil).
Num. Units	The number of heat pump units installed.
Installed Capacity	The total installed heating capacity of the installed heating system (BTU/Hr).
Is Retrofit	Whether installation was in existing or home completing construciton.
Home Address	The address of the home.
Contractor	The name and address of the contractor who worked on the project.

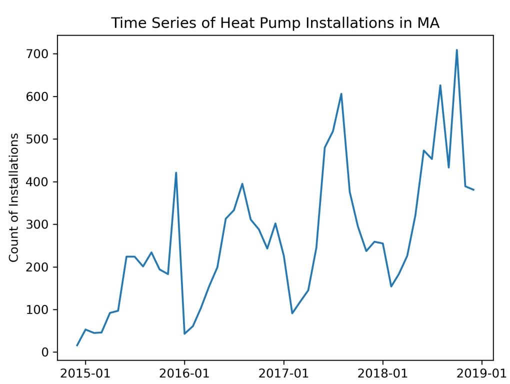
home, the total cost, the number of heat pumps, the type of previous heating system was in place, and if it was kept as a backup system (see Table 1.2).

Temporal and geographical distribution of installations

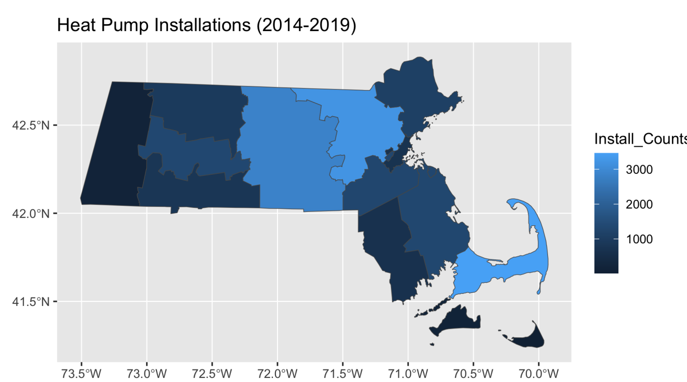
Panel a in Figure 1.1 presents the time series of installations in our sample. There is an increasing trend in installations over our sample period. There are 2,614 installations recorded in 2015 in our data and 6,258 installations in 2018. In addition, heat pump installations have a seasonal trend (Fig 1.1 a), peaking in the summer months and dipping in the winter months.

Panel b in Figure 1.1 displays the regional distribution of installations in our sample. There is a particularly high uptake of heat pumps in Barnstable, Middlesex, and Worcester counties by pure counts.

Figure 1.1: Count of Heat Pump Installations over time (a) and by Massachusetts County (b)



(a) Time series of installations



(b) Regional distribution installations

Table 1.3: Variables sourced from Zillow

Parcel Number	Uniquely identifying number of home.
Home Type	The type of home (i.e. Single Family or Multi Family).
Roof Type	The type of roofing installed (i.e. Asphalt).
Exterior Features	Primarily the exterior finish of the home (i.e. Shingle or Brick).
Construction Materials	Material used in construction (i.e. Frame or Concrete).
Living Area	Square footage of available living area.
Bedrooms	Number of bedrooms.
Bathrooms	Number of bathrooms.
Year Built	The recorded year of completion of the home.
Heating	Most recent recorded heating method of home.
Cooling	Most recent recorded cooling method of home.
Price History	Recorded prices of home when listed on the market as available to Zillow.
Tax History	Recorded tax history of home as available to Zillow.
Zestimate	Zillow's current estimate of the home's market value.

Zillow home characteristic data

Home characteristic data from Zillow, a home listing website containing information on homes sourced from public records, are used to supplement the rebate data. The postal address of the homes in the rebate dataset were used to search and scrape information off of the Zillow website. The variables collected, when available, are listed in *table 1.3*. This provides key information on the characteristics of the home used in the econometric models. Not including a variable for the year of construction, for example, could lead to conclusions that would have been explained by variation in age. Data made publicly available by Zillow has been similarly used in other research for gaining parcel-level information on properties and the neighborhoods they reside in [17], [18].

The compiled data set is a unique combination of comprehensive information about **14,396 installations** within Massachusetts executed by **627 contracting companies.**. Tables 1.4 and 1.5 provide the summary statistics of our final data set for the analysis. The average cost per installation is USD 9,367. The average installation has 2.33 heat-pump units and 29,180 BTU/hr of installed capacity. The vast majority of these installations were retrofits to *existing* homes with a previous form of heating (natural gas heating for 43% and oil-based heating for 38%). The average size of a dwelling in our sample is 1,858 square feet, with 3 bedrooms and 2 bathrooms. Houses in our sample were built between 1803 and 2019, with the average house in our sample built in 1961. The majority of houses in our sample are single-family houses (93%), with only 6% of heat pumps being installed in multifamily or condo units. The average contractor company in our data set has installed 75 heat pumps, with a range of installations going from 1 to 606 heat pumps.

Table 1.4: Numerical Summary Statistics

	Mean	**Std**	**Min**	**0.25%**	**0.50%**	**0.75%**	**Max**
Year of Installation	2017.00	0.94	2015	2016	2017	2018	2019
Total Cost of Installation	9367.50	5274.07	1000	4970	8207	12050	53000
Total num of HP units	2.33	1.40	0	1	2	3	15
Installed Capacity	29180.87	13565.33	6968	20300	25500	36407	144000
Home Square Footage	1858.14	674.70	300	1400	1800	2200	9767
Num Bedrooms	3.21	0.80	1	3	3	4	5
Num Bathrooms	1.97	0.80	1	1	2	2	5
Year Home Built	1961.07	33.91	1803	1950	1969	1985	2022
Last Sell Price	323730.69	246441.91	1	168000	292000	425000	5065500
Zestimate	613744.58	361905.19	133500	431425	563900	731175	9326400

Table 1.5: Categorical Summary Statistics

	Num. Categories	**Most Frequent**	**Frequency**
County	14	Barnstable County	3277
Town	518	Falmouth	323
Backup Fuel	5	Natural Gas	6437
Retrofit	3	Yes	15400
Contractor	637	NETR LLC	606
Home Type	8	Single Family	12652

The details in the data are used for two primary purposes: (1) the use as controls in the econometric analysis and (2) information for constructing home energy models. The questions posed in 1.6 depend upon the data being valid and detailed enough to control for varied housing attributes in the models such as the size of the home. Furthermore, the home characteristics are used for a conditional sampling method, detailed in the home energy modeling section, which similarly depends on the accuracy of the data provided. Throughout this thesis multiple robustness checks are taken to ensure that the validity of the data holds.

1.6 Central objective

The objective of this thesis is to understand the role of learning by doing in building electrification, and in doing so, better inform the policy enabling it. The analysis is broken into three sequential questions:

1. How do contractors vary in their installation practices in terms of the sizing of the heat pump system installed and the total cost of installation?
2. Is contractor behavior shifting as they gain experience through a "learning" effect?
3. How are these shifts affecting the gained private and environmental benefits of heat pump installation?

Furthermore, this work explores how policy can be better shaped to guide these outcomes. The primary contribution of this work is the estimation of learning by doing in HVAC at a time when heat pumps were an emerging technology in Massachusetts.

Chapter 2

Econometric Modeling of Learning by Doing

The two indicators available to us in the data that have tangible influence on the barriers to heat pump adoption are the total cost of the installation, and the sizing of the system installed. The econometric models for each respective variable are used to first estimate the variation between contractors, and then the effect of increasing experience coded as the accumulated number of past installations.

2.1 Methods

The estimation of the impact of contractor installation experience on the total cost of the project and installed heating capacity is undertaken through a fixed effects modeling approach. The models control for relevant characteristics of installations, such as the hedonic attributes of the home, as well as the fixed effect dummies of individual contractors, to estimate the effect of added experience (learning) on installation outcomes.

We use a fixed-effects model to estimate the relationship between added experience in heat pump installations and installation outcomes, conditional on the relevant characteristics of the home and heating system:

$$Y_{i,c,t} = \lambda_c \cdot + \tau_t + \gamma \cdot ln(Experience_{c,t}) + \beta X_i + \epsilon_{i,c,t} \tag{2.1}$$

$Y_{i,c,t}$ describes the two main outcomes describing the performance and costs of each installation in our sample: $ln(Capacity/Sqft_{i,c,t})$, and $ln(TotalCost/Sqft_{i,c,t})$ represent the log of installed capacity (per square footage) of the heating system and the total cost (per square footage) of the project for home i completed by contracting company c in time t. λ_c describes the fixed effects associated with contracting company c, and τ_t describes the time fixed effects. Our coefficient of interest is γ, which describes the changes in costs and installed capacity for each additional heat pump installation by contractor c at year t.

Lastly, β includes a vector of coefficients associated with the list of controls for characteristics of the heating system and home that are controlled for. In particular, the vector includes the size, year built, value of the property, type of house, number of bedrooms and bathrooms, and the baseline heating type in the property at the time of the heat pump installation. The standard errors are clustered at the contracting company level (c), for the purpose of capturing unobservables correlated at the contractor level.

2.1.1 Model analysis: contractor effects

The individual effect of the contractor on either total cost or installed capacity is estimated on the company level with λ_c, which are then collectively centered around 0 by subtracting the mean. A 95% confidence interval is formulated for each contractor estimate, and is considered significantly deviant from the mean if the bounds do not contain 0.

$$\left[\bar{\lambda} - \frac{1.96 \cdot std(\lambda)}{\sqrt{n}}, \bar{\lambda} + \frac{1.96 \cdot std(\lambda)}{\sqrt{n}}\right] \tag{2.2}$$

2.1.2 Model analysis: learning

The same fixed effect models for cost and capacity are used to draw inference from γ, the learning estimate. Given that both dependent variables $ln(Capacity/Sqft_{i,c,t})$ and $ln(TotalCost/Sqft_{i,c,t})$ are log transformed, and the independent predictor represents the log transformation of experience $ln(Experience_{c,t})$, the interpretation of the γ estimate is the percentage increase in the dependent variable for every one percent increase in the experience variable.

2.1.3 Model analysis: robustness checks

The key assumptions of the fixed effects models are that the independent variables included sufficiently control for the variation in cost and capacity not attributed to the contractor or their learning. In order to test the robustness of the estimates presented, controls are gradually added to the model and checked for variations in the estimate produced. Estimates that remain in the same direction and magnitude throughout various control levels are considered to be stable and accurate.

2.2 Results

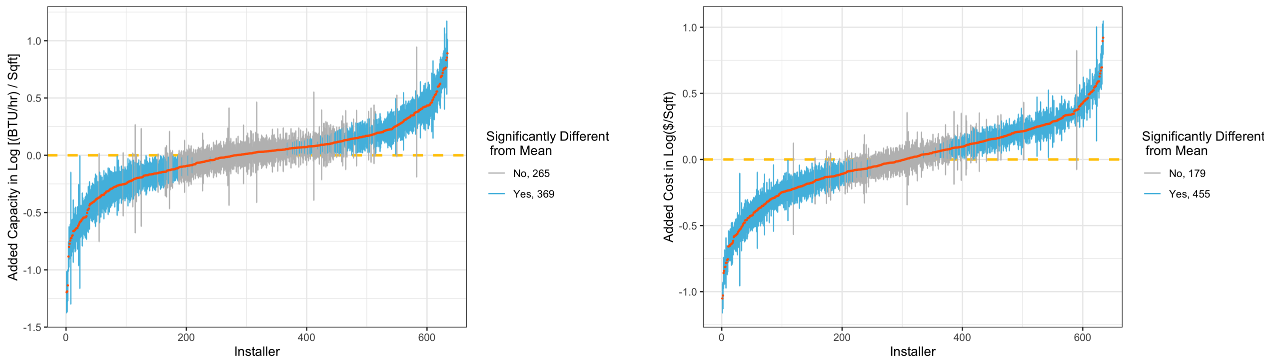
2.2.1 Contractor fixed effects

First exploring the systematic differences across contractors in pricing and installed capacity, Figure 2.1 depicts the fixed effects associated with individual contracting companies. The estimates presented are with the full set of home and installation characteristics included, further explored in the robustness checks below. Each point represents the contractor-specific average estimated added cost, holding all other control variables constant, and bars represent the 95% confidence intervals of cost for each contractor. Estimates with intervals colored in blue indicate contractors who have an estimated added cost that is significantly above or below the mean. Lastly, the dependent variables of total cost and installed capacity are standardized by the square footage of the home and log-transformed.

For a contractor's added cost, the majority of contractors significantly deviate from the mean (455 compared to 179). For the 25th percentile, the added cost is a 14.28% decrease compared to the mean across all contractors. For the 75th percentile, the added cost is 20.32% increase from the mean. Equivalently, for an average house of 1,894 square feet, with a total cost of 9,367 USD, the differences between the 25th and 75th percentile of contractor effects are \$4.2394/$Sqft$ and \$5.9505/$Sqft$ or $8,029.42$ USD and $11,270.25$ USD.

For the contractor's effect on installed capacity, 369 contractors are estimated to deviate significantly from the mean. The 25th percentile of estimates is a 13.70% decrease from the mean, and a a 16% increase for the 75th percentile.

Figure 2.1: FE Estimates by Contractor on Total Cost and Heating Capacity



(a) Added Heating Capacity (b) Added Cost

†The Y-axis is on the log scale for (Capacity/Sqft) and (Cost/Sqft). The individual estimates x are interpreted on in un-logged terms by taking the exponent (e^x), to get the multiplicative effect on the dependent variable. An estimate of -0.1541, translates to $exp(-0.1541) = 0.8572$ multiplicative effect or equivalently 14.28%

2.2.2 Learning effect on cost and capacity

Table 2.1 panel A presents the association between contractor experience and the heat-pump capacity installed in the house. The table presents our main estimates in several model specifications varying the controls and fixed effects described in Eq. 2.1. Once controlling for time effects, we estimate that added experience leads to a decrease in installed capacity. As controls for the characteristics of the home and location enter the model, this effect becomes increasingly significant and negative. For our final model (5), the interpretation for the estimates is that for each additional percentage increase in installations completed, the next heat pump the contractor installs is downsized by -0.033%. Another form of interpretation is that for every *doubling* in experience, contractors downsize systems by 2.3%.

Table 2.1 panel B presents the models that examine the relationship between the total cost of installation as the dependent variable and increased installer experience. Once controlling for time effects, the estimate for the effect of additional installation is negative, but consistently remains non-significant, with relatively large standard errors throughout various sets of controls introduced. When introducing the size of the system, the independent variable quickly captures much of the variation, meaning that total cost is unsurprisingly closely linked to the sizing of the heating equipment installed.

Table 2.1: Relationship between installer experience, installed capacity, and installation costs.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	(A) Installed Capacity Models				
Ln(Number Past Installations)	-0.026**	-0.029**	-0.031**	-0.033***	-0.033***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
DF Residuals	13,503	13,017	12,992	12,990	12,990
R-Squared	0.27	0.33	0.36	0.36	0.36
	(B) Total Cost of Installation Models				
Ln(Number Past Installations)	-0.011	-0.018	-0.020	-0.021	0.011
	(0.013)	(0.014)	(0.014)	(0.014)	(0.0072)
Ln(Installed Capacity)	-	-	-	-	0.94*** (0.0093)
DF Residuals	13,503	13,017	12,992	12,990	12,989
R-Squared	0.34	0.38	0.4	0.4	0.84
	Controls				
Installer FEs	Yes	Yes	Yes	Yes	Yes
Year Installed FEs	Yes	Yes	Yes	Yes	Yes
Month Installed FEs	Yes	Yes	Yes	Yes	Yes
Hedonic Controls	Yes	Yes	Yes	Yes	Yes
Town FEs	No	Yes	Yes	Yes	Yes
Previous Heating Controls	No	No	Yes	Yes	Yes
Heat Pump Brand	No	No	No	Yes	Yes

$***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.2: Comparison of learning estimate in individual and combined models.

	(1) *Company Only*	*(2)* *Individual Only*	*(3)* *Town Only*	*(4)* *Combined Model*
Company Level	-0.033*** (0.012)	-	-	-0.039*** (0.011)
Individual Level	-	-0.026*** (0.0090)	-	0.0049 (0.0053)
Town Level	-	-	-0.035*** (0.013)	-0.021 (0.015)

†Controlling for installer, time, town, previous heating source, heat pump type, and hedonics.
$***p < 0.01, **p < 0.05, *p < 0.1$

2.2.3 Level of learning

The results reported above were made with the previous installations variable being counted on the *contracting company level*. The availability of data allows us the alternative to test whether the learning effect is stable, and if it is stronger, when counting previous installation experience on the individual employee level and the town level. Table 2.2 contains the results from running the models with all controls included as individual learning estimates, and as a combined model.

Models (1) to (3) show that the effect of system size reduction as a function of experience is decreasing on all levels, and is highest in magnitude for the company-level. Model (4) includes all coded levels in a "horse-race", with the company-level effect winning out. Interestingly, this finding corresponds with the previous research done on photovoltaic installations done by Bollinger and Gillingham, where learning was on the company-level [15].

2.2.4 Heterogeneity analysis

Next, we test the learning effect on data partitioned by the type of previous heating system in place. This has particularly important implications for the MassCEC rebate program because most homes kept their previous form of heating as a backup heating system. Due to the availability of data, results are shown in table 2.3 by the two primary heating sources: natural gas and oil, followed by all remaining types gathered as "Other".

When partitioning models by the backup fuel source, the learning effect with regard to

Table 2.3: Heterogeneity analysis of learning effect across fuel types.

	(1) *All Types*	*(2)* *Natural Gas*	*(3)* *Oil*	*(4)* *Other*
	(A) Outcome: Installed Capacity			
Ln(Number Past Installations)	-0.033*** (0.012)	-0.045** (0.021)	-0.026 (0.016)	-0.014 (0.031)
Observations	12990	4409	5001	2025
R-Squared	0.36	0.79	0.76	0.90
	(B) Outcome: Installation Cost			
Ln(Number Past Installations)	-0.021 (0.014)	-0.046** (0.021)	-0.0076 (0.020)	-0.0081 (0.033)
Observations	12990	4409	5001	2025
R-Squared	0.41	0.80	0.78	0.91

†Controlling for installer, time, town, previous heating source, heat pump type, and hedonics.
$***p < 0.01, **p < 0.05, *p < 0.1$

installed system capacity holds for natural gas, and increases in magnitude. When doing this partition for the total installation cost models, the learning effect becomes significant for natural gas as well. What this means is that contractors are downsizing system size over time particularly for homes with natural gas backups, and this in turn is driving down the total cost of installation.

2.3 Discussion

The econometric models are used as a tool to make comparisons between contractors across different homes and installations. While comparing the size of a heating system between two differently sized homes may not be valid, doing so over several hundreds of homes, and controlling for variables like size and age, makes the comparison viable. From the fixed effects models we have learned that (1) contractors are varying significantly from one another in terms of cost of installation and sizing of the system. (2) Observing this over gained experience, contractors are decreasing the size of systems over time across all fuel types. (3) When sub-setting to homes with natural gas backup heating, the learning effect on downsizing is stronger, and decreases in cost become statistically significant. (4) These decreases in cost are explained primarily by the reductions in the size of the system.

While these results shed light upon the direction of change, questions on whether behavior is converging to some optimal size or cost is not yet answerable. Furthermore, the impact of this shifting behavior on the total operational cost and end use emissions cannot be determined without further building energy modeling. The following chapter explores these questions.

Chapter 3

Home Energy Modeling and the Learning Curve

Our previous estimates indicate that the contractors are decreasing the total size of the systems as they gain experience. The impact of the reduction is unclear without knowing the heating needs of a home. Past research into the sizing of HVAC equipment point towards systems being initially oversized to guarantee that the home's full heat demand can be met [10], [19]–[21]. System overisizing leads to higher upfront costs for unnecessarily large equipment, and reductions in operational efficiency through duct leakage and low-load cycling [21]. Learning to reduce cases of oversizing would increase the quality of heat pump installations. This implies that in the learning process contractors first install larger heat pumps than necessary, and then begin to decrease size to match the actual heating needed. The results of the building energy demand models covered in this chapter, however, suggest that the heating systems were undersized to begin with, and continued to decrease with experience. The following policy chapter investigates the structure of the MassCEC rebate program that can explain this finding.

In order to simulate the heating needs of the homes in the rebate data, the known characteristics of the homes are used in conjunction with conditionally sampled building models made possible through ResStock: a state-of-the-art tool developed by the National Renewable Energy Laboratory (NREL). ResStock combines data from multiple sources including the EIA's Residential Energy Consumption Survey (RECS) to create high-resolution conditional probability tables for home characteristics like square footage, insulation, window-type, HVAC type, and HVAC efficiency [22]. The use of full characteristics with the OpenStudio and EnergyPlus modeling framework makes foundational work towards predicting energy demand and its corresponding challenges across the United States possible [23]–[25].

ResStock and its resulting expected energy demand outputs are used to evaluate the sizing of the *actual* installed heat pump systems. The modeling is done in three key steps:

1. **Housing Stock Characterization:** The definition of the building stock. The national ResStock profile targets the residential buildings in the 48 contiguous states of the U.S. This paper subsets to characteristics that match the Massachusetts homes within the rebate data.

2. **Statistical Sampling:** A representative sample of home characteristics are sampled, conditional on the definition of the housing stock. For the purposes of this work the housing stock is characterized by location, the age of the building, and the square footage (i.e., Massachusetts homes built in 1970-1979 that are between 1500-2000 square feet in size).

3. **Baseline Building Simulations:** Characteristics of homes are facilitated by the OpenStudio software to be fed into EnergyPlus building energy simulation to assess the heating and energy needs of homes.

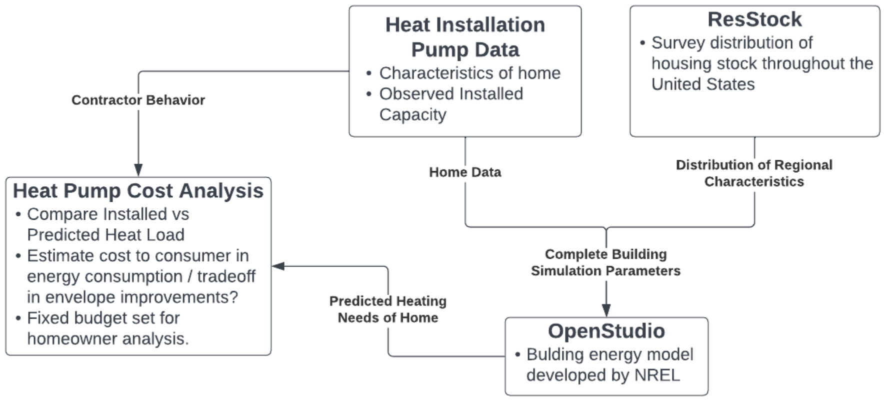
The advantage of using ResStock in combination with existing heat pump installation data is that the missing characteristics needed to simulate heating needs for comparison can be reliable sampled by *conditioning on the characteristics we do have* and then simulated through EnergyPlus. Details on sampling are in the following section.

3.1 Methods

3.1.1 Home sampling

The homes in the heat pump installation data are grouped by their characteristics to subsequently be sampled for in ResStock. For example, the most common grouping of homes in

Figure 3.1: Home Energy Modeling Flow



the data are ones that were built before 1940 and have a floor area between 1500 and 1999 square feet. This grouping covers 931 homes in the data. Conditional on the location, time built, and floor area size, we use ResStock to return a representative sample of 100 homes that match the description, which are then simulated for a year's worth of energy data.

The histogram in 3.2 compares the ***design heat load*** for the subgroup of home energy models (i.e. the magnitude of heat the heating system must output to keep the home at the set point temperature [usually 70° F)]) and the ***Installed Capacity at 5° F*** in our data. There are **766** installations that match the group description.

The specificity of groupings can be increased, with characteristics like roof material (asphalt, wood shake, etc.), exterior material (brick, wood, etc.), and number of bedrooms, showing the most promise in terms of availability. Increasing the specificity of groupings, however, multiplicatively increases the number of sampling and simulations that must be conducted by the dimension of the variable. The 10 categories of home age and 9 categories of home size results in $(10 \cdot 9 = 90)$ subgroups, which are each sampled and simulated 100 times from ResStock, resulting in approximately 9000 simulations. Due to limitations in time and computation, the housing stock was not specified further, but portability to high performance computing systems is available through ResStock.

Figure 3.2: Comparison between the installed capacity and design load for heat pump homes that were built in the 1980's and are between 1500-1999 sqft. in size.

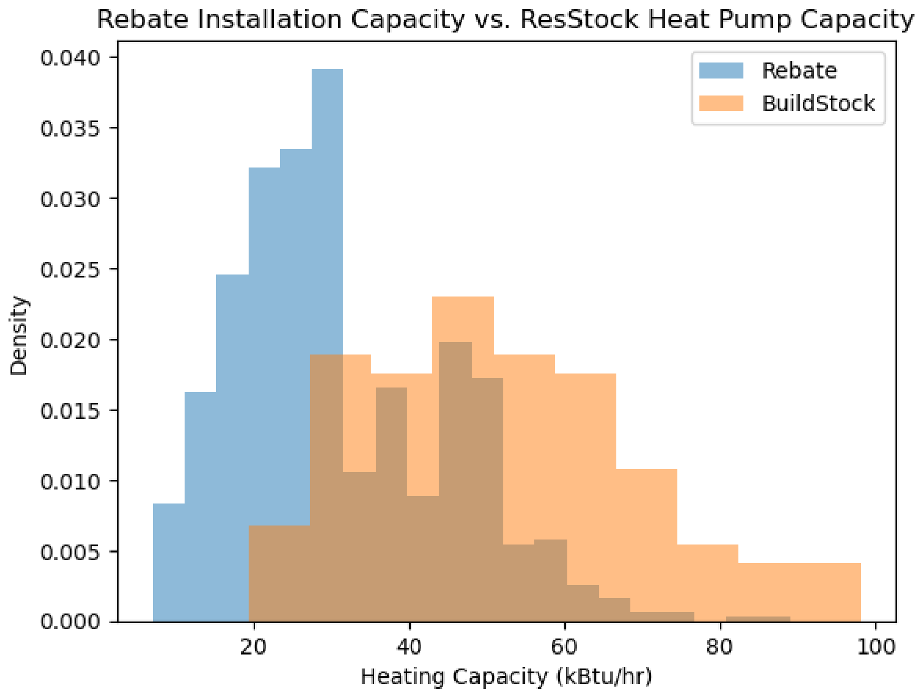


Table 3.1: Ten most prevalent combinations of home vintage and floor area bin in Massachusetts heat pump data.

Home Age Subgroup	**Floor Area Subgroup**	**Count**
<1940	1500-1999	931
1980s	1500-1999	766
<1940	1000-1499	751
1970s	1500-1999	729
1950s	1000-1499	709
1960s	1500-1999	613
1970s	1000-1499	591
1980s	2000-2499	565
1950s	1500-1999	537
1980s	1000-1499	520

3.1.2 Inability to evaluate sizing of heat pump system through installed and simulated capacity comparison

The most direct method of judging the sizing of the system installed is by comparing the heat load of the home, and the optimally sized pump to meet that load, to what was actually installed. The core issue is that **most homes kept their previous heating system** from a lack of incentive structure to remove them. The lack of information on the size of the previous heating system, and the usage strategy for it as a backup, makes direct comparisons impractical. The distributions in figure 3.2, for example, suggest that the rebate distribution is largely undersizing relative to the simulated ResStock heat load. With the right amount of information on the size of the backup heating system, the combined heating capacity of the heat pumps installed in the rebate program could be shifted rightwards to compensate, but no such data is available.

3.1.3 Measuring quality of installation by load hours

The alternative to judging the sizing of the actual installed systems is measuring the number of hours in which the heat pumps can sufficiently supply heat for a typical weather year. This is done using the specific model number of the heat pumps recorded in the rebate data, which are then matched up to the North East Energy Efficiency Partnership (NEEP) heat pump database. Table 3.2, shows the data for a given model. Notably, heat pump performance varies across outdoor conditions, with minimum and maximum heating capacities decreasing at lower outdoor temperatures.

Given information on the heat pumps, the second piece to understanding the sizing is the heating needs of the home. The ResStock simulations are used to estimate the ***design heat load***: the heat load the heating system must output to keep the home at the set indoor temperature [such as 68° F] at the ***design temperature*** (which the ACAA Manual J sets at the temperature at which 99% of the expected hourly temperatures in a typical weather year are above for that location).

Specifically, ResStock is used to generate heat loads for 100 homes, which are taken as a balance between addressing the uncertainty inherent in conditionally sampling models for

Table 3.2: Heating and cooling capabilities for a Mitsubishi Electric M-Series H2i, model number SUZ-KA12NAHZ

Heat/Cool	**Outdoor Temp**	**Indoor Temp**	**Unit**	**Min**	**Rated**	**Max**
Cooling	95F	80F	Btu/h	5,770	12,000	12,000
			kW	0.34	0.85	0.85
			COP	4.97	4.14	4.14
Cooling	82F	80F	Btu/h	6,300	-	12,300
			kW	0.26	-	0.72
			COP	7.1	-	5.01
Heating	47F	70F	Btu/h	7,900	15,000	18,000
			kW	0.48	1.1	1.39
			COP	4.82	4	3.8
Heating	17F	70F	Btu/h	4,500	9,000	15,000
			kW	0.46	0.97	1.62
			COP	2.87	2.72	2.71
Heating	5F	70F	Btu/h	3,300	-	15,000
			kW	0.45	-	2.1
			COP	2.15	-	2.09

a single home and having a reasonable computational demand. For each of the head load estimates for a home, a *heat load line* is constructed to measure the installed heating systems capabilities throughout a typical weather year.

Figure 3.3 (a) depicts the estimated heat load line for an example home that has a heating set point temperature 60° F. At the design temperature of 15° F, the home requires approximately 4500 BTU/hr to maintain the 60° F set point. As a simplification, the load is assumed linear, and is 0 when the outdoor temperature is the same as the heating set point. Similar linear assumptions have been discussed in the literature [26].

The heat load line is then used to assess the capabilities of the installed heat pump system. The variable capacity heat pumps installed as a requirement for the Mass CEC rebate have a functional range of heat output at various rated temperatures. Each variable capacity heat pump has a minimum and maximum BTU/hr output capacity, which varies by model and outdoor conditions. Given the rated capacities, the ***modulating range*** is the space where the installed heating system can serve the heating demand of the home. Once the heat load line is above the maximum capacity of the system, a backup heat source is needed, marked as the ***backup heat range***. When the heat load line is below the minimum

Table 3.3: Cost to produce heat in Massachusetts winter 2023/24 by heating technology.

Heating Technology	*$ Cost per MBtu*	*Cost per Unit of Fuel*
Natural gas furnace	24.91	$2.04/therm
Air-source heat pump	32.03	$0.33/kWh
Oil furnace	40.27	$4.36/gal
Propane heating	50.33	$3.59/gal
Electric resistance	96.12	$0.33/kWh

heating capacity, the heating system will begin to low load cycle, meeting heat demand at a lower efficiency. Figure 3.3 (b) displays the ranges for the example home.

An average weather year is matched to the location of the installation, and is used to evaluate the number of hours in which the installed system is able to meet the full demand in the modulation zone, and when it is insufficient and in the backup heat zone. The mean is taken across the 100 simulations per matched actual installation.

Aside from the count of hours in each zone, the ratio between backup heating hours and modulating hours is taken as a reference of heating hours served by the electric heat pump system to the hours served using fossil fuels. The log-transformation is taken in the regression model to better fit the normality assumption.

$$\text{Backup Ratio} = \frac{\text{Backup Hours}}{\text{Modulating Hours}}$$

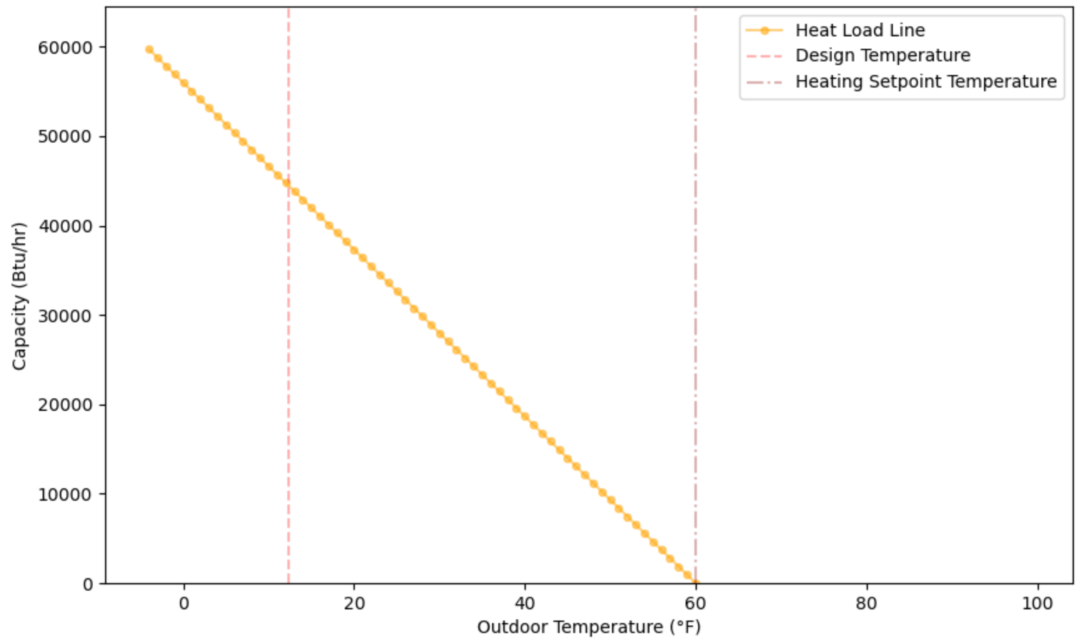
3.1.4 Calculation of emissions and annual fuel costs

Emissions and annual fuel costs per heating fuel are estimated to assess the wider impact of system downsizing and increases in backup heating hours. The Massachusetts Department of Energy Resources reports the cost per million Btu by heating technology[27], shown in table 3.3.

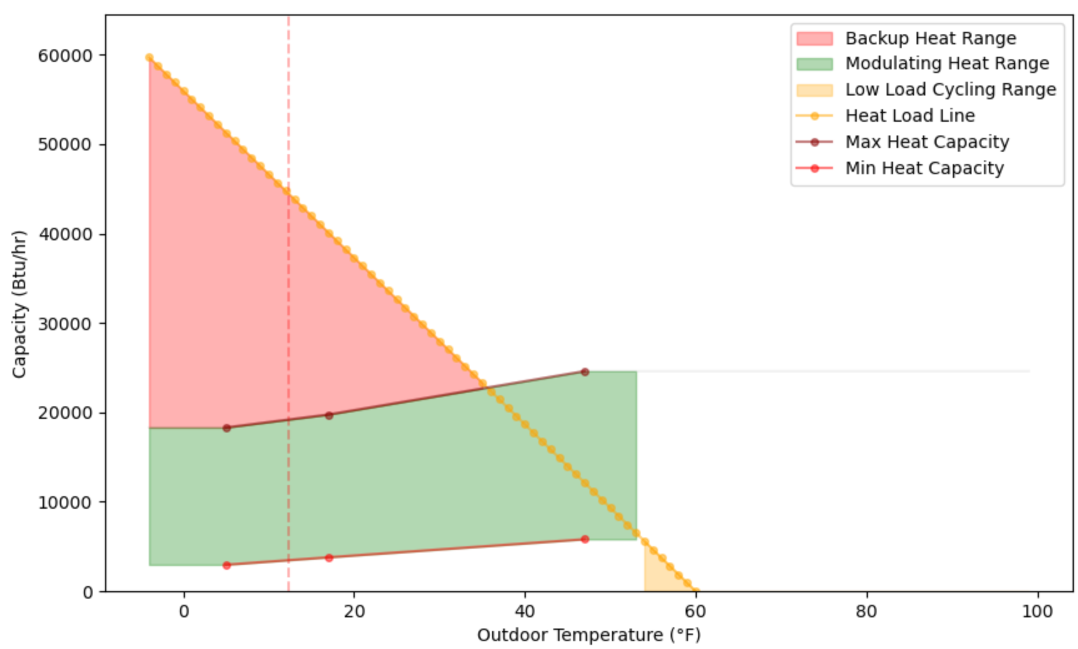
Estimating the emissions by energy type is split by heating from electric sources (heat pumps and electric-resistance), and fuels (natural gas and oil). The latter does not vary from state-to-state, and is provided directly in terms of kg of CO2 emissions per million Btu in residential and commercial buildings by the U.S. Energy Information Administration [28].

For electric-based heating, the emissions estimates are subset to the Massachusetts elec-

Figure 3.3: Relationship between outdoor temperature, heat load, and installed system for example home.



(a) Heat load line relative to design temperature and heating set point.



(b) Heat load line relative to installed system capabilities.

Table 3.4: Emissions associated with producing heat in Massachusetts winter 2023/24 by heating technology.

Heating Technology	*kg CO2 per MBtu*
Natural gas furnace	52.91
Air-source heat pump	42.01
Oil furnace	74.14
Electric resistance	126.00
Electric resistance	96.12

tric grid, and are prone to speculation based on the varied sources of electricity generation. The conversion is made in two steps: (1) the derivation of kWh consumed per $MBtu$ for an air source heat pump (eq. 3.1) and electric resistance heater (eq. 3.2) and (2) multiplication by the average kg CO2 produced per kWh of electricity produced for Massachusetts. Below is step (1) using the technology-specific costs from Mass DOER:

$$\frac{\$32.03}{MBtu} / \frac{\$0.33}{kWh} = 97.1 \frac{kWh}{MBtu} \tag{3.1}$$

$$\frac{\$96.12}{MBtu} / \frac{\$0.33}{kWh} = 291.3 \frac{kWh}{MBtu} \tag{3.2}$$

$$\frac{9,098 \text{ kTons CO2}}{21,026,161 \text{ MWh}} = 0.0004327 \frac{TonsCO2}{kWh} \tag{3.3}$$

The total net generation from the Massachusetts Electricity Profile for 2022 [29] is divided by the kilotons of CO2 produced to produce the average emissions per kWh of electricity in equation 3.3. The estimates by technology are in table 3.4[1]. Finally, each cost and emission coefficient is multiplied by the total Btu served by the backup heating system over a year.

3.1.5 Learning model for heat load hours

Given the hours in each heat load zone and the backup ratio, the same regression-based model described in equation 2.1 is used to estimate the learning effect on heating outcomes. Notably the outcomes to direct backup hours and modulation hours are unaltered, while the

[1]Projected goals from the MassSave program set Tons CO2 emissions per MWh at 0.1869 for 2025 and 0.1065 for 2030.

ratio is log-transformed to better support the assumption of normality. Similar heterogeneity analyses are conducted across fuel types to examine the relationship between fuel costs and observed learning behavior.

3.2 Results

Table 3.6 compares the impact of learning on (1) the annual number of hours in which a *simulated* backup heating system is needed, (2) the annual number of hours in which the *simulated* heat pump system can sufficiently supply the heat demand for a home, and (3) the ratio of the two. For every 10% increase in the number of installations a contractor completes, we estimate a multiplicative increase of 5.38 in backup hours[2]. The learning effect on modulation hours is not statistically significant, but the ratio between the two is in favor of increases in backup hours. This implies that as contractor experience increases, the shift in heat pump size reductions is coming at the cost of more hours being served by the backup system, increasing the overall portions of the year in which fossil-fuels are still being used for space heating.

Table 3.5: Comparison of learning effects across cost, capacity, and heating hours.

	(1) *Backup Hours*	*(2)* *Modulation Hours*	*(3)* *Ln(Backup/Mod Ratio)*
Ln(Number Past Installations)	56.46*	-22.70	0.053**
	(33.49)	(22.48)	(0.022)
Observations	11424	11424	11424

$***p < 0.01, **p < 0.05, *p < 0.1$

The heterogeneity analysis across fuel types is shown in table 3.6. An ongoing thread of results pertaining to natural gas backups having a stronger correlation to learning effects persists. The following question is whether the differences in the cost and emissions between natural gas and other fuel sources can be seen through the lens of experience. The impact of learning on these outcomes split by BTU/hr for each heating technology is in table 3.7.

[2] Due to the natural log transformation of the independent variable, the interpretation is produced as: $ln(1.10) \cdot 56.46 = 5.38$

Table 3.6: Relationship between backup hours to modulation hours: $Ln(Backup/Mod)$, by previous heating fuel.

	(1) *All Types*	*(2)* *Natural Gas*	*(3)* *Fuel Oil*	*(4)* *Electric Resistance*
Ln(Number Past Installations)	0.053**	0.082**	0.017	0.018
	(0.022)	(0.039)	(0.032)	(0.094)
Observations	11424	3817	4527	862
R-Squared	0.83	0.95	0.93	0.85

$***p < 0.01, **p < 0.05, *p < 0.1$

Across all heating fuels, operational cost and emissions estimates are increasing as contractors gain experience. When sub-setting to homes with natural gas backup systems, the effect is again stronger. The implications of this are discussed in the next section.

Table 3.7: Realized impact of learning on annual cost and emissions by backup heating source.

	(1) *All Types*	*(2)* *Natural Gas*	*(3)* *Oil*	*(4)* *Electric Resistance*
	(A) Outcome: Ln(Annual Fuel Cost)			
Ln(Number Past Installations)	0.011*	0.016**	0.0077	-0.00076
	(0.0056)	(0.0066)	(0.0075)	(0.043)
	(B) Outcome: Ln(Annual Emissions)			
Ln(Number Past Installations)	0.014**	0.022***	0.0088	-0.00076
	(0.0062)	(0.0075)	(0.0087)	(0.043)
Observations	10378	3813	4523	862

$***p < 0.01, **p < 0.05, *p < 0.1$

3.3 Discussion

Prior to the home energy demand models, contractors were observed to be downsizing as they gain experience, but information to whether behavior was converging to an optimal heat pump sizing was unknown. With ResStock, we know that the heat pump systems were undersized for serving the whole heating demand of homes to begin with, and continue to decrease in capacity. The key question is if this "learning" behavior reaching some optimal goal, or is it going in the wrong direction?

The MassCEC rebate allowed homeowners to keep their previous heating system as a backup heating source. Additionally, the rebate was on a per-unit basis, meaning that qualifying cold climate heat pumps would receive the same amount regardless of individual unit size. Looking at the most recent year of data available at the time of writing, natural gas was the cheapest source of heating per million Btu of heating in Massachusetts, followed by air source heat pumps, heating oil, and finally electric resistance heating (table 3.3) [27].

In the short-term, downsizing heat pumps to allocate more annual hours to a natural gas backup would decrease costs, as opposed to doing so for other, more expensive fuel sources. This strategy coincides with the findings specific to natural gas: the learning effect on downsizing and increased backup hours is consistently stronger.

Chapter 4

Policy Analysis and Conclusion

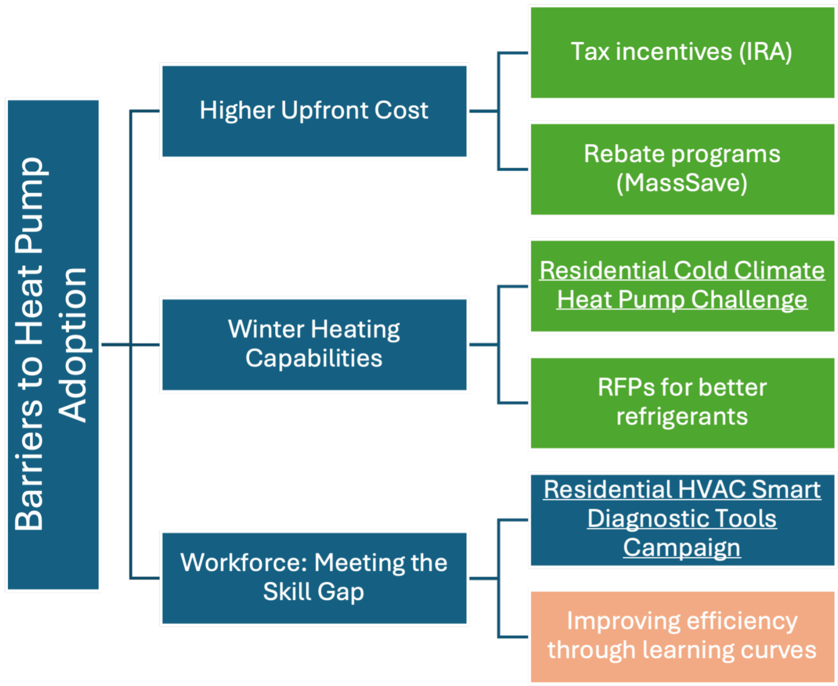
4.1 Economics of incentivizing heat pump adoption

The use of fossil-fuels for space heating makes up the majority of on-site emissions in buildings [1], and heat pumps are the primary technology set to replace gas and oil-based heating. A barrier to heat pump adoption is the higher upfront cost of installation relative to replacing an existing gas or oil furnace [4], which subsidy programs seek to address. Incentive programs have been used to promote adoption for earlier green technologies like electric vehicles (EVs) and rooftop solar installations, providing potential guidance for incentivizing heat pump adoption.

An initial concern from incentive programs is that they may not reach the target population, and subsidize adoption for wealthier households or "free-riders" who would have adopted the technology without the program. For US clean energy tax credits (2006-2016), Borenstein and Davis found that "the bottom three income quintiles have received about 10% of all credits, while the top quintile has received about 60%" [30]. This results in two negative outcomes: economic inefficiency from spending tax credits on households that were already inclined to adopting, and the distributional impact of subsidies not reaching low income households. Though heat pump rebates are similarly structured as previous green subsidy programs, the distribution of their adoption varies in some fundamental ways.

Recent work shows that there is little correlation between heat pump adoption and household income in the United States, and instead the correlation lies with geography, climate,

Figure 4.1: Heat pump adoption barriers and policy interventions.



and electricity prices [8]. High electricity prices are negatively correlated with adoption, highlighting the importance of fuel costs [8]. Notably, the intensity of the cold climate described through *Heating Degree Days* (HDD) has a negative correlation with adoption in the US, but is positively correlated with adoption in the European Union [8]. The southern United States therefore has high rates of adoption, with Alabama, North Carolina, and South Carolina having about 40% of homes heated by heat pumps [8].

While this mitigates concerns around the distributional effects of the subsidy by income, it emphasizes factors observed to be working against adoption in Massachusetts: a cold climate, high electricity prices, and low natural gas prices. The latter becomes a key point in understanding the reasons for downsizing observed in the rebate data. In Massachusetts the average cost per kilowatt hour is 33 cents, as opposed to 7 cents per equivalent kilowatt hour in natural gas [27] [1]. Subsidies like MassCEC's and MassSave target the *upfront cost* of a heat pump installation, but not the *operational cost* driven by the price of fuel. Adjustments to electricity rate design to make heat pumps cost-competitive with natural gas, however, is

[1] A better comparison is not cost per kwh, but cost per BTU, which accounts for the differences in heating efficiency between a natural gas furnace and a heat pump.

outside the scope of this thesis[2].

Finally the overall efficiency of the subsidy must be put to question. The economic justification behind subsidies towards technology adoption like solar panels and heat pumps is that the cost of subsidization will be equal to, or less than the societal benefit from a reduction in negative externalities (i.e., GHG emissions) [16]. Benthem, Gillingham, and Sweeney found that for the California Solar Initiative, the societal benefit (in the form of US dollars) from reductions in GHG emissions through solar panel adoption only made up for a small fraction of the cost of the subsidy [16]. With a modest progress ratio in installer learning of 0.9, signifying that for every doubling in solar panels installed the non-hardware cost drops by 10%, the paper finds that the existing subsidy is near optimal [16]. The existence of learning by doing therefore is a primary motivation for the subsidy, and can play an important *positive* role in the justification for subsidized heat pumps. The correct utilization of LBD through the MassCEC subsidy and future building electrification programs, is essential to achieving net-zero emission goals in an economically effective manner.

4.2 The direction of learning and misaligned incentives

The previous two chapters indicate that heat pumps are being downsized as contractors gain experience, and the effect is strongest for homes that have a natural gas backup system. Furthermore, the home energy models reveals that this shift comes at the cost of more heating hours served by fossil-fuel backup heating, increasing annual emissions from the learning baseline. If the intention of the rebate program was to reduce emissions and increase full building electrification, the learning by doing externality, which worked in favor of the California solar initiative, works against the MassCEC program's goal.

Such instances of misaligned incentives set by electrification and efficiency programs has been observed before. Allcott and Greenstone examine the implications of realized gains from two Wisconsin incentive programs in their working paper "Measuring the Welfare Effects of Residential Energy Efficiency Programs" [31]. First, they find that the programs under-

[2] Thesis work done by Graham Turk at the MIT Energy Initiative does look into this challenge, however, and should be considered.

delivered on gained home energy efficiency, realizing only 68 percent of the engineering model predictions [31]. Energy savings falling short of expectation are not a new finding, and reflect a pervasive view of an "energy-efficiency" gap between expected and actual energy savings in home energy efficiency programs[32]. The paper goes further to indicate potential reasons for the shortcomings, and structural improvements to the rebate program. Notably, the authors identify a *misalignment* between the goals of the subsidy and its spending, created by subsidizing energy use across all heating fuels and home sizes equally [31]. What this means is that the goals of the program, to reduce GHG emissions and the negative externality it imposes on society, did not maximize its dollars spent towards reducing the externality. The structure favored smaller homes that already had lower GHG emissions, and ignored the large differences in emissions produces by heating fuel type. If the program *had* distinguished between the size and heating fuel source of homes, the authors estimate that the programs would have generated four times the gains, partially in the form of carbon abatement [31]. This misalignment in program structure points towards sub-optimal program spending, but what about installer behavior?

Misalignment in subsidy program structure has also been shown to influence contractor behavior. In the California Energy Savings Assistance (ESA) program, which provided appliance upgrades for low-income households, contractors were paid a small fee to conduct an energy audit for eligibility, and a larger fee to install the appliance if the home was eligible [33]. Motivated by the discrepancy in compensation, the author found that for contractors that both completed the energy audit and appliance installation, the rate of misreported eligibility was more than doubled (7.8% to 19%) compared to cases where the tasks were done by separate contractors [33]. The structuring of the rebate program therefore had important impact on incentivized behavior, and the realized benefits of the program. Unqualified appliances that were subsidized for replacement reduced energy consumption by 30% less than qualified ones [33].

This thesis distinguishes itself from the energy-efficiency gap and incentives literature by incorporating the learning by doing aspect for heat pump technology. Even when the oversizing of HVAC systems is the prevalent issue in the industry [10], [19]–[21], the structure of the rebate, allowing for backup systems to remain in place, and compensating homeowners per-unit independent of capacity, created incentives to where upfront installation costs and short-term fuel cost could be decreased by undersizing the heat pump systems.

4.3 MassSave and alternative rebate structures

After the MassCEC rebate program ended in 2019, it was followed by the Mass Save program, which also provides heat pump rebates. Notably, the incentive structure changed, only providing the full rebate amount to whole-home heating replacement, and a capacity-based rebate otherwise (table 4.1). A short analysis is done on data on the 163 homes that installed heat pumps through the Mass Save program for which data is available.

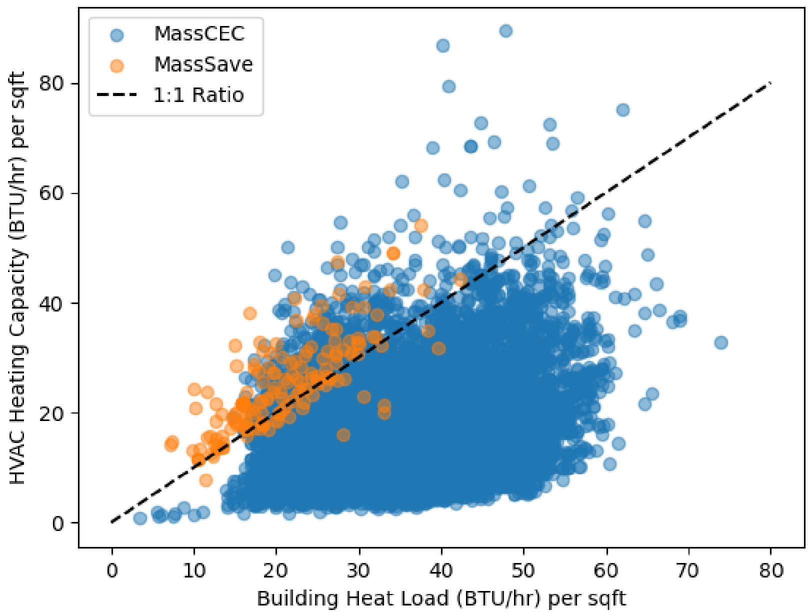
Table 4.1: Mass Save Rebate Compensation Structure

Rebate Type	Rebate Amount
Whole-Home	$10,000 per home
Partial-Home	$1,250 per ton up to $10,000

The Mass Save program involved more detailed data collection, allowing the direct comparison of peak building heat load, calculated through an energy auditing process prior to installation, to the full installed capacity of the heating system (figure 4.2). When the full replacement of heating *is* incentivized, the majority of installations we observe in Mass Save, which lie above the 1:1 line, are sized at, or larger than the expected heating demand. When compared to the installed capacity vs simulated heating demand of the MassCEC rebates, the majority of the installations are below the 1:1 ratio line, suggesting undersized heat pumps which need a backup to meet full heat demand.

The differences that can be seen from this short analysis is clear, but exactly what to do about it is not. Did the change in Mass Save's structure solve the problem? What lessons can be learned for future incentive programs? These questions are explored further in the final section.

Figure 4.2: Home heating needs per square foot to installed capacity of heating systems in MassCEC and Mass Save rebate programs.



4.4 Considerations for future policy

The importance of learning by doing has been a mainstay throughout this thesis. If utilized properly, it can reduce the future costs of deploying new technologies, and can make up a substantial benefit to expensive subsidy programs. With large amounts of federal money being spent on energy efficiency and electrification through the Inflation Reduction Act, it is as important as ever to be intentional about the direction of learning by doing.

The MassCEC program saw LBD go in the direction of reducing upfront costs of installation, and the short-term fuel cost of heating. This thesis is not here to say that this LBD direction is wrong, but that contractor learning *is* happening and should be considered when structuring policy. The macro-level tradeoff between more hours of natural gas use and increased demand on the electric grid is complex and ongoing. "Fixing" the misalignment in displacing fossil-fuel heating would entail a large increase in electric heating demand from Massachusetts' current grid, which has not been decarbonized. Whether the five years of learning under the MassCEC rebate will have any significant effect from re-learning under the MassSave program is a future direction of research.

The MassCEC program was also early, starting in late 2014, bringing possible questions on the capabilities of heat pumps at the time. While single-speed heat pumps struggle cold climates, the MassCEC program was forward-looking and required variable-speed, cold-climate capable heat pumps that *are* fully capable of serving full heating demand when sized properly [34]. Technology at the time therefore *could* keep up to a full replacement alternative.

Finally, I make three recommendations for policy that can align with the decarbonization goals of building electrification:

1. **Consider the heating fuel that the heat pump is displacing.** This has an impact on the operating cost that the electric heat pump will have to compete with, and the externality posed by the continued burning of that fuel. For Massachusetts, we have seen that heating oil is both more expensive than electricity and produces higher GHG emissions per million BTU produced than natural gas, making it a low-hanging fruit for displacement by heat pumps.

2. **Consider the suitability of the building for heat pump installation.** Heat pumps rely on an effective building envelope for proper function, and as a result, a large amount of time was spent on ensuring the heating demand of homes was properly modeled through ResStock. The discussion on investments made towards improved home insulation vs heating fuel switching is ongoing [24], and deploying heat pumps in buildings where they can be most effective again ensures program dollars well spent.

3. **Consider the role of learning, and its impact on new technologies.** This can take on many forms, but past thinking about the alignment of incentives with program goals, subsidies could be tiered, paying more towards early-learners that can bring the largest savings.

Appendix A

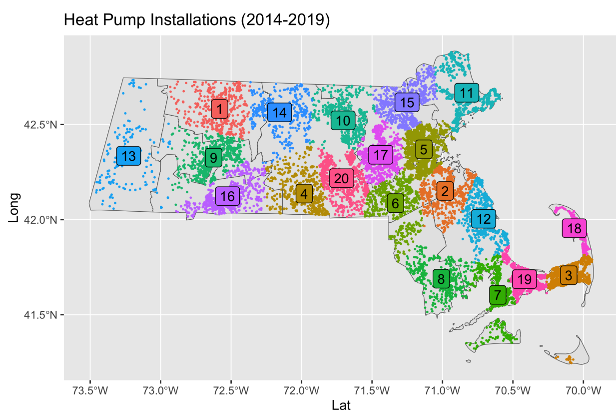
Appendix

A.1 Analysis on market competition

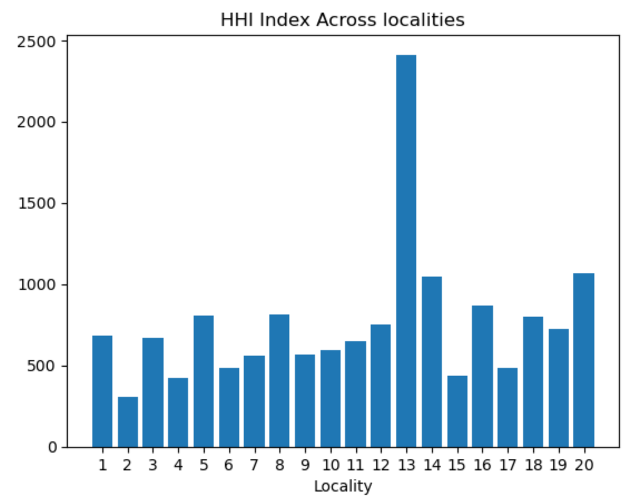
A final aspect of the data to be explored is the spatial distribution of heat pump installations within Massachusetts. The eyeball observation is that there are clear clusters of installers' contracts, and it seems that many of the installers operate quite locally. This bears interest in the context of contractors because contractors who operate near each other are presumably competing in the same market for installations. In order to measure this, we use the HHI index, a commonly used measure of market concentration [35]. HHI values below 1,500 are considered unconcentrated industry, and HHI ranges between 1,500 and 2,500 are considered to have moderate concentration [35]. Here, we group the heat pump installations into 20 sub-markets through K-means clustering, and calculate the HHI index for each sub-market, as shown in figure A.1.

All submarkets sit below the 2,500 mark, informing us of a reasonable enough level of competition in each locality for consumers to have a reasonable choice across competitors. The location with the highest amount of market concentration is locality 13, with an HHI of 2,411, which is in the far west of Massachusetts and has the lowest density of installations. The lowest amount of concentration is seen in locality 2, in the Boston area, with an HHI 306. Low market concentration is not exclusive to the Boston area. However, areas such as localities 15 and 4 are in less dense areas of Massachusetts and still have high levels of market competition.

Figure A.1: HHI Index Across selected 20 Sub-Markets



(a) Locality Clustering Map



(b) HHI Values per Locality

Colors in figure (a) represent the localities in which HHI was calculated. Localities were determined through K-means clustering from point address locations of completed heat pump installations across Massachusetts.

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