How Much Does It Really Cost?
A Dynamic Approach to Building Retrofit Costs for Decarbonization Pathways

by

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BA, Physics
Middlebury College, 2019

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ABSTRACT

Carbon emissions are driving the planet out of its delicate Goldilocks balance. Evidence and the call-to-action date back to 1896 with Swedish scientist Svante Arrhenius and his seminal paper that first predicted the effect of carbon dioxide on the global temperatures. With the Intergovernmental Panel on Climate Change (IPCC) goal of global net zero emissions by 2050, the urgency is stronger than ever. An ever-growing number of municipalities are setting pledges to do their part, often without a concrete plan. With buildings accounting for 40% of total global emissions, building retrofits are a key component to these pathways to zero carbon. Urban building energy modeling (UBEM) research efforts have developed physics-based decision-making tools to define city-scale technology pathways to reach climate goals. However, a crucial question in making these pathways actionable has been largely neglected: *how much does it really cost?* The scarcity of contemporary cost data and methods for cost prediction at the urban scale makes this question difficult, and further questions around equitable incentive programs nearly impossible to answer. This work demonstrates the concept and relevance of implementing a dynamic cost model in the UBEM context. Several cost models are applied to a case study of 13,000 residences in Oshkosh, WI to predict costs for homeowners to retrofit their homes with three different upgrade packages. A willingness to pay analysis is then performed with upfront cost predictions from different models, illustrating the impact a more robust cost model may have in providing more realistic predictions of an upgrade strategy's techno-economic success. Through its compatibility with existing UBEM frameworks and local input costs, the dynamic building upgrade cost model hosts the potential to further support municipalities in developing economically feasible building retrofit strategies for decarbonization pathways.

Thesis Advisor: Christoph Reinhart

Title: Professor of Building Technology

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Acronyms

ASHP – Air Source Heat Pump

ATB – Annual Technology Baseline

DER – Deep Energy Retrofit

DOE – U.S. Department of Energy

EE – Energy Efficiency

GBT – Gradient Boosted Trees

HP – Heat Pump

HSEF – High Sierra Energy Foundation

HSPF – Heating Seasonal Performance Factor

IEA – International Energy Agency

IECC – International Energy Conservation Code

IPCC – Intergovernmental Panel on Climate Change

LED – Light Emitting Diode

MassCEC – Massachusetts Clean Energy Center

MIT – Massachusetts Institute of Technology

NEEP – Northeast Efficiency Partnership

NREL – National Renewable Energy Laboratory

PV – Photovoltaics

REMDB – Residential Energy Measures Database

SEER – Seasonal Energy Efficiency Ratio

UBEM – Urban Building Energy Modeling

VEIC - Vermont Energy Investment Corporation

WHHP – Whole-Home Heat Pump Pilot

XPS – Extruded Polystyrene Foam Board

All images created by author unless otherwise noted.

1. Introduction

Carbon emissions are driving this planet we call home out of its delicate Goldilocks balance. This is nothing new, with evidence and calls to action around climate change dating back to 1896 with Swedish scientist Svante Arrhenius and his seminal paper that first predicted the effect of carbon dioxide on the global temperatures (Arrhenius, 1896). The Intergovernmental Panel on Climate Change (IPCC) has set forth that the global temperature rise must be kept under 1.5°C to limit the most catastrophic impacts of climate change (Calvin et al., 2023). In order to reach this goal, the world as a collective must reach net zero emissions by 2050 (International Energy Agency, 2022).

An ever-growing number of municipalities across the globe are setting pledges to do their part to achieve net zero carbon emissions; however, the pathways set forth by these municipalities to achieve these goals are not always as concrete. With buildings accounting for 40% of total global carbon emissions, building retrofits are a critical component in the pathway to net zero emissions (International Energy Agency, 2023). Building retrofit measures generally fall into three categories: envelope, equipment, and photovoltaics (Less et al., 2021). Within each category, a wide range of upgrades exist from simple energy conservation measures to deeply intensive upgrades that can take months to complete. For example, for envelope upgrades, there is simple weatherization—such as air sealing, weatherstripping, simple storm window installation —and there is full deep energy retrofit (DER) of the envelope, such as adding continuous external insulation to the whole facade.

Building energy modelling has long been used as a tool to evaluate energy performance at the individual building-level scale and optimize combinations of building retrofit measures for optimal energy and carbon emission reductions. On the state and national scale, the ResStock analysis tool by the National Renewable Energy Laboratory (NREL) has been used to define decarbonization technology pathways for residential sector in the U.S. (Berrill et al., 2022). Energy modeling at city-scale in the form urban building energy models (UBEMs) is becoming more valuable than ever to assist in developing technology pathways to assist municipalities in achieving their ambitious decarbonization goals (IISD, 2019). An eight-step simulation-based framework developed by Berzolla et al. involves the development of a baseline UBEM and applying packages of energy efficiency upgrades to buildings of different archetypes. The method allows for municipal policy makers to explore technology pathways that will reduce annual carbon emissions in existing buildings (Z. Berzolla, Ang, et al., 2023).

In this way, the development of technological pathways to building decarbonization at all scales are relatively well defined; however, a crucial question in making these pathways actionable has been largely neglected: *how much does it really cost?* Cost of building upgrades play a significant role in the adoption of building retrofit strategies. With upfront costs of a deep energy retrofit being upwards of $50,000 per home, a homeowner's willingness to pay becomes largely dependent on the total cost of the project compared to income and a variety of other factors (Cluett & Amann, 2014). At a building level analysis, costs of upgrades are analyzed by contractors and firms using privately maintained databases or for-purchase services, such as RSMeans by Gordian, a database service that provides current construction costs with material, labor and/or equipment prices and at the unit, assembly or square foot level of detail for 970 U.S. locations nationwide (Gordian, 2020; Sigrist et al., 2019). At the national and state scale, costs from the NREL Residential Energy Measures Data Base (REMDB) are considered in ResStock analysis tool (Berrill et al., 2022). The NREL Residential Energy Measures Data Base (REMDB) was developed to provide a national unified public database of residential building retrofit measures and associated costs based on the 2014 Building America House Simulation Protocols (Wilson et al., 2014). As the only database of its kind, the NREL REMDB is the current industry standard; however, its age and use of national average costs makes it only applicable for national and state scale models. The scarcity of contemporary cost data and methods for cost prediction at the urban scale makes the question, *"How much does it really cost?"* difficult to answer, and further questions around equitable incentive programs nearly impossible.

When it comes to incorporating a cost parameter into an UBEM analysis framework to optimize for the most cost-effective, feasible pathway to net zero building carbon emissions, many approaches fall short. In a review of the 2023 International Conference Proceedings of Building Simulation 2023, 18th Conference of the International Building Performance Simulation Association (IBPSA), 16 papers discussed urban building energy modeling in some capacity, none of which included a cost element as a parameter in the UBEM framework (Lara Arambula, Carnieletto, and Pasut 2023; Auf Hamada, Raslan, and Hong 2023; Li, Wang, and Xu 2023; Song et al. 2023; Park et al. 2023; Zhao and Mo 2023; Fennell et al. 2023; Kourgiozou et al. 2023; Piro, Ballarini, and Corrado 2023; Cruz, Bastos, and Caldas 2023; Geagea and Saleh 2023; Pan, Yu, and Zhou 2023; Rachman et al. 2023; Ju and Moura 2023; Shen et al. 2023; Lin et al. 2023). In Cruz et. al., the authors mention cost in the future work section: "to better understand each design solution's feasibility, the cost should be integrated into the optimization process" (Cruz et al., 2023). A few papers include a statement acknowledging the importance of economics in grounding the feasibility of the technology pathways set forth leveraging an UBEM framework; however, even in these cases, no concrete parameters of the cost of upgrades are included (Calvin et al., 2023; Lara Arambula et al., 2023; Park et al., 2023). Expanding the review, only one paper concerning UBEMs from the 2022 Conference Proceedings for the Building Performance Analysis Conference and SimBuild, a U.S. based IBPSA conference, includes cost as a qualitative, subjective parameter in the modeling framework, stating "a detailed cost assessment was not a scope of work for the case study presented, and the cost metrics provided for a typically quantitative column are reduced to a subjective scale" (Baliga & Gilles, 2022).

Progress towards city-level decarbonization goals depends on each household's decision to act. Without reliable individual building cost estimates, technological pathways to decarbonization are ships dead in the water unless they are applied in tandem with a financial model. The resulting technoeconomic UBEM has the potential to become a powerful decision-making tool for policy makers and city officials to deploy limited funds towards incentive programs in an effective manner. Generating a cost estimate tailored to the physical characteristics of each home with a dynamic cost model offers a significant opportunity to provide detailed insight into potential impact of incentives in removing financial barriers to retrofit adoption.

Previous work by Berzolla et. al. characterized a static cost model for a series of building upgrade packages proposed for urban decarbonization pathways (Z. Berzolla, Ang, et al., 2023; Gordian, 2020). For this static cost model, upgrade costs are calculated for two typical buildings of the same size, one pre-1980 and one post-1980, based on values from the NREL REMDB database and RSMeans (Gordian, 2020; NREL REMDB, 2018). This static set of costs was then applied to all residential buildings city-wide. While a static model such as this one may provide an estimate at the overall magnitude of capital required to retrofit the building stock at the city level, an individual homeowner's willingness to pay for a building retrofit crucially depends on their particular upfront costs along with household income, education, concern for the environment and other factors (Z. Berzolla, Meng, et al., 2023). Without cost predictions tailored to the specific building characteristics for each homeowner for their local urban setting, predictions of the homeowner's willingness to pay for a given set of upgrades is highly inaccurate.

This work demonstrates the concept of implementing a dynamic cost model in the urban building energy modeling context and its potential impact on carbon reduction pathways. In Section 2, we first define a dynamic cost model and outline our proposed approach. This includes the definition of more involved cost model component for complex upgrades, including photovoltaics and heat pumps. We then apply different cost model approaches to estimate upgrade package costs for an existing UBEM of 13,000 residential homes in Oshkosh, WI. These includes three dynamic models using different cost inputs—area-based, area-age based, and inputs sourced solely from the NREL REMDB—and a static model. Finally, we analyze the impact of these cost predictions on individual homeowners' willingness to pay to illustrate the potential impact a dynamic cost model may have on a city's carbon emission reduction pathway.

2. Methodology

We begin with a brief description of the urban building energy model (UBEM) process (Reinhart & Cerezo Davila, 2016). In the UBEM process, the details of each real building are simplified to a 2.5-dimensional model. Buildings are then grouped into archetypes based on similar construction sets and program type. For example, all single-family homes may be grouped into archetypes based on the year they were built. This categorization operates under the assumption that buildings constructed in eras aligning with local building code are likely to still share similar characteristics for wall construction and thus thermal performance. Each archetype is then layered with the inputs required for the physics-based calculations performed by energy modeling engine, Energy Plus™. These inputs include building construction sets, schedules, occupancy, equipment and lighting power densities, infiltration, water usage, and other values. Archetypes may be linked to Department of Energy Prototype Building Models that are linked to national and international building standard evolutions, such as ASHRAE Standard 90.1 and IECC, or by custom templates developed from local knowledge (ASHRAE, 2022; International Code Council, 2021; U.S. Department of Energy, 2024b). With the goal to integrate a dynamic cost model into this UBEM framework, the following cost model approaches are developed and analyzed within this world of 2.5-D modeling.

In developing technology pathways for building retrofits, building-level characteristics are used to model the carbon emissions reduction potential for different retrofit upgrade packages (Ang et al., 2023). In this process, energy consumption and potential energy savings are calculated for each building based on archetype templates, then summed to calculate the total energy usage and carbon emissions of the city. To be actionable, these upgrades must have costs associated with them. The static cost model approach accompanying previous work by Berzolla calculates upgrade costs for typical buildings in each archetype and assigns these as fixed unit costs to all buildings of a given archetype. While useful for quick city-wide cost estimates, this “one size fits all” approach fails to capture the nuances at the building level that cause significant variations in costs between homes of varying dimensions. We propose a dynamic approach to calculate a tailored cost for each building-based building components and metrics, as shown in Figure 2.1.

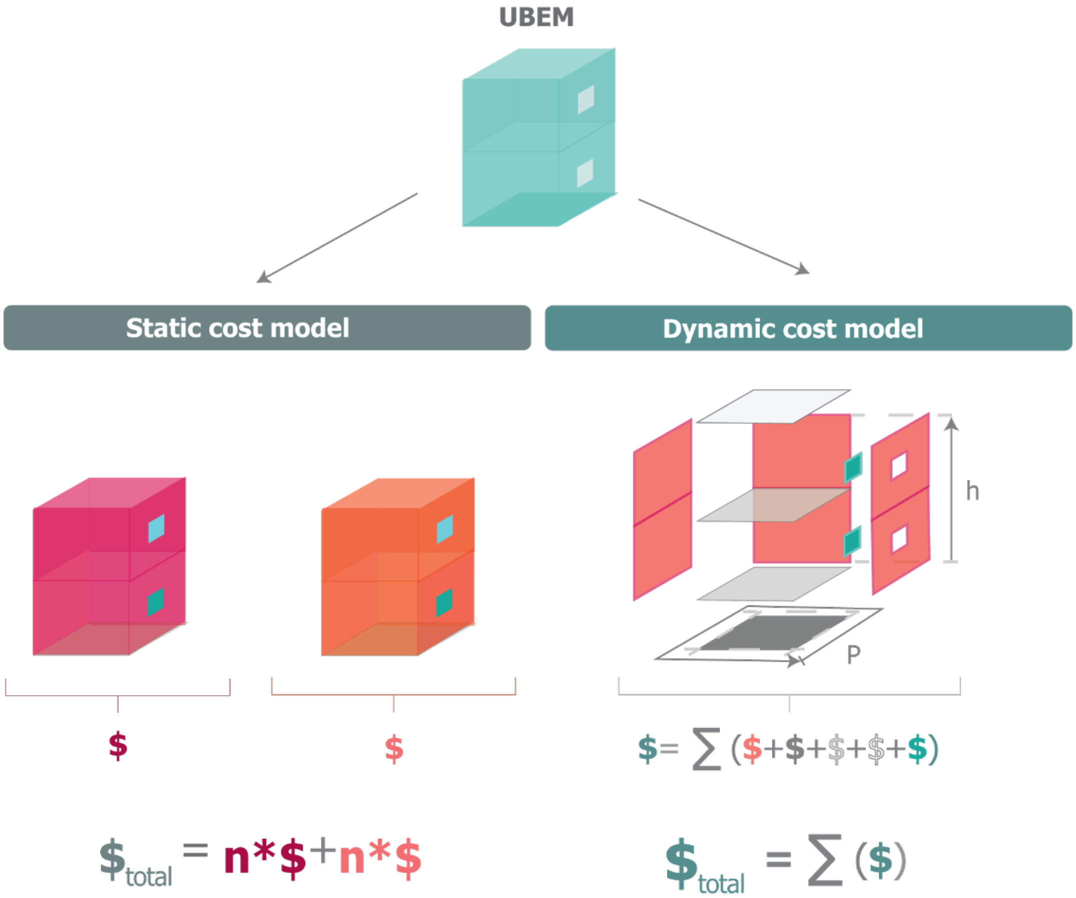

Figure 2.1 Comparison of static and dynamic cost model approaches.
The dynamic approach calculates a tailored cost for each building based on information extracted from the urban building energy model, whereas a static approach applies a single cost to each archetype.

2.1.Definition of the Dynamic Building Upgrade Cost Model

In the proposed dynamic building upgrade cost model, the costs for each building upgrade are divided into building-component level cost elements, defined by the equations below. By using the same building component characteristics used in UBEM-level upgrade energy simulations, this framework can be integrated into an existing UBEM workflow.

Input costs can be sourced from any available data source. This enables urban scale building retrofit cost analysis informed by relevant regional cost inputs available, preferably with installation, labor, and other soft costs included. The few building upgrade cost databases currently available—the National Renewable Energy Laboratory (NREL) Residential Energy Measures Database (REMDB) and RSMeans by Gordian (Gordian, 2020; NREL REMDB, 2018)—are tied to cost per unit of upgrade material or building metric, such as dollars per square foot of insulation or dollars per kBtu for heat pumps. While these sources have limitations for urban-level analyses since they pertain to national averages—which we will discuss in detail in Section 4—they set the industry standard for how input costs are structured for professional building-level construction cost estimation. Thus, we use this structure to inform the structure of the dynamic cost model defined below.

For upgrade costs related to total conditioned floor area, such as a lighting upgrade with cost inputs given in dollars per square foot living area, a floor cost component is included:

$$C_{floor} = C_{sfla} * A_{building}$$

Where:

- C_{floor} is floor area cost in dollars (\$)
- C_{sfla} cost per unit area of upgrade material (\$/m^2)
- $A_{building}$ is total conditioned floor area of the building (m^2)

The roof area cost component encompasses upgrades concerning the roof and attic areas, such as attic insulation and photovoltaic array installation. In the 2.5-D modeling context, this is:

$$C_{roof} = C_r * \frac{A_{building}}{F}$$

Where:

- C_{roof} is roof area cost in dollars (\$)
- C_r is cost per unit area of upgrade material (\$/m^2)
- $A_{building}$ is total conditioned floor area of the building (m^2)
- F is the number of floors

A footprint cost is calculated similarly for building footprint upgrades, such as slab insulation:

$$C_{footprint} = C_f * \frac{A_{building}}{F}$$

Where:

- $C_{footprint}$ is footprint area cost in dollars (\$)
- C_f is cost per unit area of upgrade material (\$/m^2)
- $A_{building}$ is total conditioned floor area of the building (m^2)
- F is the number of floors

For upgrades concerning envelope, such as improvements to wall insulation, an envelope cost component is determined as follows:

$$C_{envelope} = C_e * P * H * (1 - \frac{WWR}{100})$$

Where:

- $C_{envelope}$ is envelope area cost in dollars ($)
- C_e is cost per unit area of upgrade material ($/$m^2$)
- P is perimeter of the building (m)
- H is height of the building (m)
- WWR is window-to-wall ratio (%)

For window upgrades, a window area cost component is calculated as:

$$C_{window} = C_w * (P * H * \frac{WWR}{100})$$

Where:

- C_{window} is window area cost in dollars ($)
- C_w *is* cost per unit area of upgrade material ($/$m^2$)
- P is perimeter of the building (m)
- H is height of the building (m)
- WWR is window-to-wall ratio (%)

For upgrades that have a single fixed unit cost per installation, such as the upgrade to an ENERGY STAR appliance (i.e. one-time purchase of the appliance) or other fixed cost elements for other upgrade installations, the unit costs are summed for all upgrades applied to the building:

$$C_{unit} = \sum_{i=1}^{n} (C_u)$$

Where:

- C_u represents the unit cost for an individual upgrade.
- n is the total number of upgrades for each building.

For heat pump installations, additional considerations, such as building age, number of rooms, and peak heating load may be required for more accurate cost predictions. For the clarity and cohesiveness of the dynamic model definition here, we discuss in more detail the different model approaches for cost predictions specifically regarding air source heat pumps in Section 2.2, and refer to this cost component as $C_{heat\ pump}$ here.

For each upgrade, a cost for each of the above components is calculated, with any irrelevant cost components equal to zero. For example, as in the case of the NREL REMDB heat pump model, there is a fixed unit cost, a peak heating load cost component, and a number of rooms component. These would all be calculated using the respective source cost inputs, with all other cost components being equal to zero. Summing the cost components over all the upgrades, we achieve a prediction of the total cost of the upgrade package for the given building:

$$C_{building} = \sum_{i=1}^{n} C_{floor} + C_{roof} + C_{footprint} + \ C_{envelope} + C_{window} + C_{unit} + C_{*})$$

Where:

- $C_{building}$ represents the total cost for an individual building.
- n is the total number of upgrades for each building.
- C_{floor}, C_{roof} , $C_{footprint}$, $C_{envelope}$, C_{window}, C_{unit} are the respective cost components for each upgrade.
- C_{*} represents the respective cost for complex upgrades, such as air source heat pumps and photovoltaics.

Summing the individual building costs over all buildings in the city,

$$Total\ Cost_{city} = \sum_{i=1}^{k} (C_{building})$$

Where:

- $C_{building}$ represents the total cost for each building.
- k is the total number of buildings in the city.

2.2.Modeling Complex Upgrade Costs: Photovoltaics

The cost of photovoltaics (PV) has extensively been studied by researchers at NREL with a quarterly benchmark report on cost trends in the solar industry (NREL, 2024). The benchmark considers both system hardware costs and soft costs, such as labor, permitting, and overhead costs to determine cost in dollars per watt of residential and commercial PV systems. In the dynamic cost models, we utilize the 2021 benchmark of \$3.03 per watt for residential PV systems. Thus, the resulting cost component is:

$$C_{PV} = C_{capacity} * E_{load}$$

Where:

- C_{PV} is PV system cost in dollars (\$)
- $C_{capacity}$ cost per unit capacity of the system (\$/W)
- E_{load} is total electrical load of the building (kWh)

2.3.Modeling Complex Upgrade Costs: Heat Pumps

Electric heat pumps are a hot topic in current efforts toward building decarbonization. The appeal of energy savings from deep building retrofit façade upgrades pales in comparison to the sexy, modern heat pump. It is an easier sell to any homeowner to install a heat pump in a day rather than face the dreaded disruption and displacement required for the walls of their home to be ripped open and stuffed with more insulation. Furthermore, the visibility of a mini-split heat pump is a point of pride to any homeowner, much like photovoltaics. Not only are they easier to install than upgrading facades, but they are also a high-impact, purchasable item that governments can easily incentivize. Objectively necessary for the full decarbonization of the heating and cooling loads of the building sector, the allocation of \$169 million by U.S. Department of Energy million to expedite the manufacturing of electric heat pumps is no surprise (Amarnath, 2023). In the words of U.S. Secretary of Energy Jennifer Granholm, "Since 2011, DOE's Better Buildings Initiative has helped paved the way for cost-effective energy efficiency and decarbonization solutions across America's building sector. Our new Commercial Building Heat Pump Accelerator builds on more than a decade of public-private partnerships to get cutting edge clean technologies from lab to market, helping to slash harmful carbon emissions throughout our economy" (U.S. Department of Energy, 2024a). With this attitude by the current federal administration, it is clear heat pumps will continue to be key players in urban decarbonization pathways. Energy initiatives across the U.S. are responding accordingly by rolling out resources to educate homeowners on why a heat pump is right for them and accompanying incentive and rebate programs (Efficiency Vermont, 2024a; MassCEC, 2021; MassSave, 2024; Northeastern Energy Partnership, 2023). In the urban building energy modeling context, a study by Ang et. al. proposing retrofit scenarios in eight-cities across the globe includes heat pumps in three of eight scenarios (Ang et al., 2023).

However, the cost of heat pumps remains a major barrier to adoption. Despite the multi-million-dollar initiatives being devoted to improving the "cost-effectiveness" of equipment and incentivize homeowners to buy heat pumps, it is a significant investment for the majority of homeowners. Additionally, whether a homeowner qualifies for incentives and rebates is another significant factor in the willingness of a homeowner to invest in such an expensive upgrade. According to a survey and analysis by Purdy in 2022, heat pump installations in the U.S. costs between \$3,500 and \$20,000, depending on the size of their home, with an average cost of about \$14,000, even after rebates (Purdy, 2022). The average cost of a heat pump in a Massachusetts single-family home was at the higher end of this spectrum at \$18,400, according data collected as part of the Massachusetts Clean Energy Center's (MassCEC) Whole-Home Heat Pump (WHHP) Pilot, which ran from May 2019 through June 2021, (MassCEC, 2021). Based on the study by Purdy, costs vary greatly depending on location, size of the home, number of zones, age of the home, prior system, existing ductwork, and if a need for an electrical upgrade. With such a wide range of costs and so many contributing variables, it is unclear how much capital it would take to implement the heat pumps alone required for decarbonization pathways.

In the context of the proposed dynamic cost model defined in Section 2.1, a more involved approach is needed to predict the cost component for the complex upgrade of heat pump installations. We examine a small set of real project installation cost data for 160 homes in Massachusetts collected through the Mass Save® whole-home heat pump installation rebate program and compare the performance of four different models in predicting the installation costs for heat pumps in Massachusetts. The *static heat pump model* is simply the average cost for installations in the state of Massachusetts and is incorporated into the cost model as fixed unit cost.

The *area-based heat pump model* utilizes the estimated cost per sq. ft. conditioned floor area, according to the MassCEC WHHP Pilot (MassCEC, 2021).

The Mass Save® real heat pump project cost data includes basic information about the home, including age, total conditioned floor area, previous system information, design heating load, and detailed information on the number and type of units installed. Costs are reported as sub costs, including system hardware (i.e. material and equipment costs) and soft costs (i.e. labor and administrative costs). A distribution of total project costs normalized by conditioned floor area and sorted by total material and equipment costs, with a break down by sub cost, is shown in Figure 2.2. Material and equipment costs per square foot vary significantly from project to project, ranging from less than 5 dollars per square foot to 20 dollars per square foot of conditioned floor area. Soft costs, largely labor and removal of the previous system, vary widely project to project.

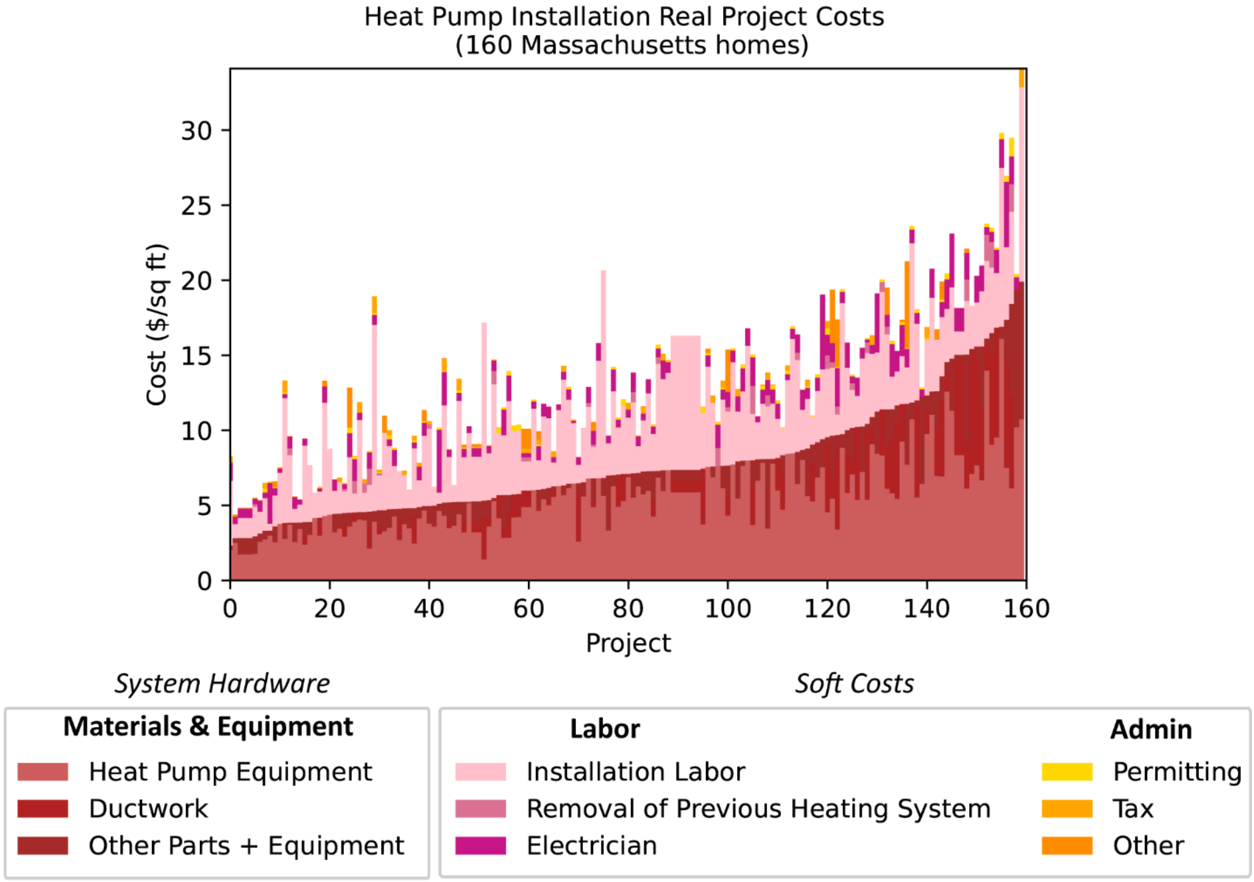

Figure 2.2. Breakdown of real heat pump installation project costs in Massachusetts. Total cost of installations for 160 homes in Massachusetts are divided into sub costs, categorized as Materials & Equipment, Labor, and Administrative Costs. Each column corresponds to a single installation project. Costs are normalized by the total conditioned floor area and then sorted by total equipment costs.

The variation in this visualization indicates that more is at play in determining project costs than just square footage, requiring a more detailed dynamic cost model component than a simple *area-based* approach. For all features in the dataset, feature importance in determining Total Installed Project Cost was analyzed using a Gradient Boosted Trees (GBT) approach, as described by Adler and Painsky (Adler & Painsky, 2021). Results of this analysis are shown in Figure 2.3, along with a visualization of the impact of key features on cost—total conditioned floor area, peak load, and year built.

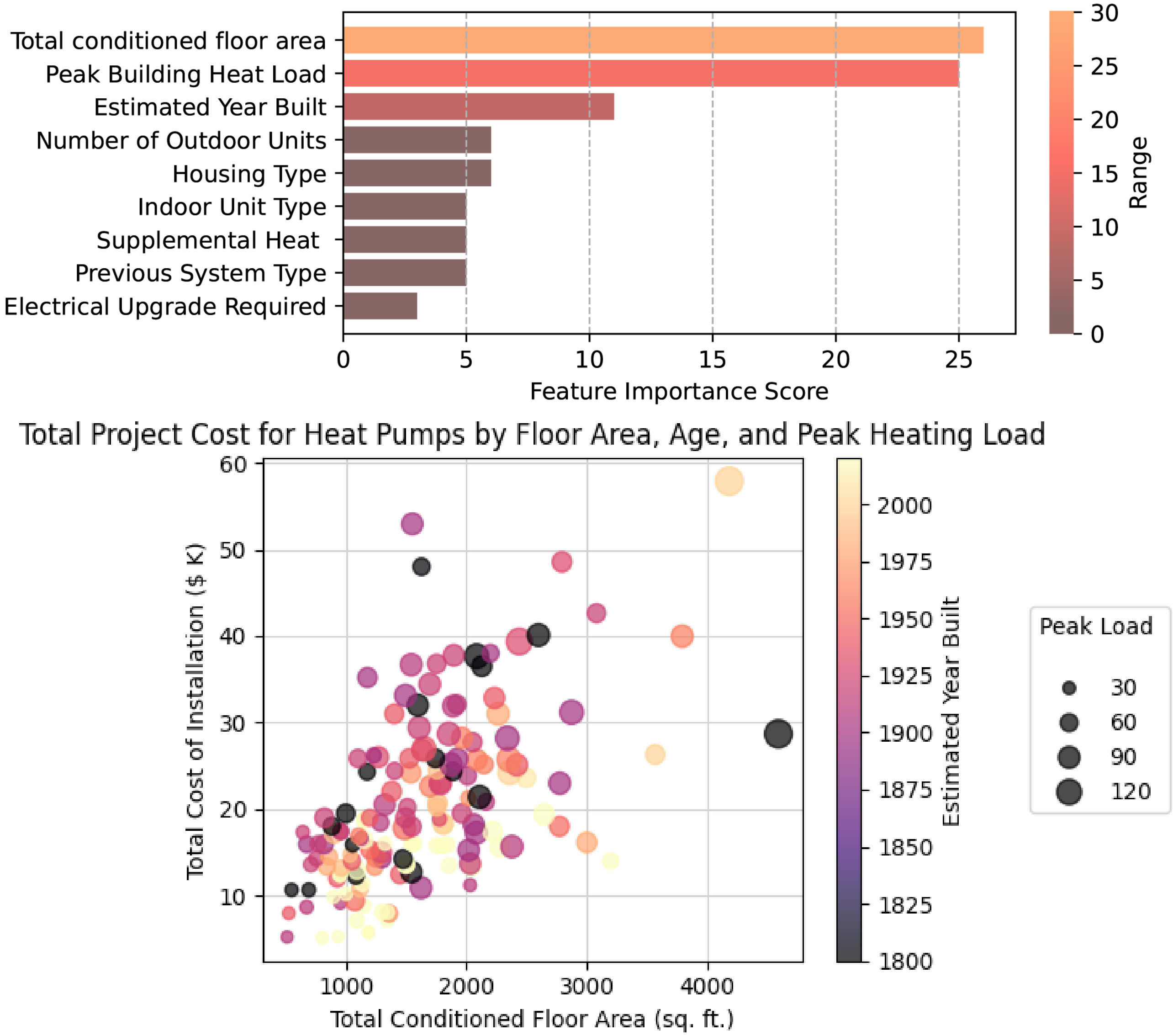

Figure 2.3. Factors influencing heat pump installation costs.

Results from a feature importance analysis using the gradient boosted trees (GBT) machine learning method on a dataset of 160 heat pump installations in Massachusetts. Key features include floor area, year built, and peak load. Total costs are plotted with these key data features considered.

With peak building heat load being directly correlated to the climate and all homes being in the same climate, we perform a simple linear regression to between Total Estimated Project Cost and two parameters: total conditioned floor area and year built. This serves as the proposed *area-age-based heat pump* model, with the resulting cost component being:

$$C_{ashp,area-age} = 4134.77 + 46.31 * Y_{age} + 7.73 * A_{building}$$

Where:

- $C_{heat\ pump}$ is air source heat pump system cost in dollars ($)
- Y_{age} is the age of the building in (years)
- $A_{building}$ is total conditioned floor area of the building (m^2)

For the *NREL REMDB* model, costs are determined using the NREL REMDB (NREL REMDB, 2018). Costs in the database are based on previous system, unit type and efficiency rating, peak heating load, and zones hosting units. The REMDB also includes cost estimates for removal of systems. Based on the previous system information on type and whether the system was removed as part of the project, this cost component is also included. The installed system information available in the dataset allowed for the unit type and the efficiency ratings of seasonal energy efficiency ratio (SEER) and heating seasonal performance factor (HSPF) to be determined referencing the Northeast Efficiency Partnership (NEEP) Cold Climate Air Source Heat Pump List (NEEP, 2023). This can be translated into an equation for the heat pump cost component as:

$$C_{ashp,nrel} = C_{removal} + C_{zone} * U + C_{load} * K_{heating\ load}$$

Where:

- $C_{heat\ pump}$ is air source heat pump system cost in dollars ($)
- $C_{removal}$ is the fixed unit cost for removal of previous system ($)
- C_{zone} is the cost per unit needed for each zone ($/zone unit)
- U is the number of zones
- C_{load} is the cost per unit heating design capacity ($/kBtu)
- $K_{heating\ load}$ is the heating design capacity for the building (kBtu)

Table 1. Summary of Heat Pump Cost Models

Heat Pump Model	**Cost Component Equation** $C_{heat\ pump}$	**Data Source**
Static	$\$18{,}400$	MassCEC WHHP Pilot
Area-based	$120 * A_{building}$	MassCEC WHHP Pilot
Area-Age based	$4134.77 + 46.31 * Y_{age} + 7.73 * A_{building}$	Mass Save®
NREL REMDB	$C_{removal} + C_{zone} * U + C_{load} * K_{heating\ load}$	NREL REMDB

Each of these three heat pump models, summarized in Table 1, are then applied to the sample of projects to assess performance in cost prediction. The mean absolute percentage error between predicted costs and real costs is calculated as a metric of performance. Each of these models is then used to inform the $C_{heat\ pump}$ cost component in the dynamic building upgrade cost model outlined in Section 2.1, resulting in three dynamic cost models and applied to an existing UBEM, as described in the next section.

2.4. Upgrade Cost Model Comparisons for Building Upgrades in Oshkosh, WI

To compare the predictions of the cost model approaches defined above, we consider an existing UBEM of 12,300 residential homes in Oshkosh, WI developed in previous work by Berzolla (Z. M. Berzolla, 2021). Berzolla defines three packages of building upgrades for this urban scale analysis: *Energy Efficiency*; *Energy Efficiency and Heat Pump Installation;* and *Energy Efficiency, Heat Pump Installation, and Photovoltaics*. We apply the four defined cost models —*static, NREL REMDB area-based, area-age based* —to each of these package as outlined below.

The existing static cost model deployed by Berzolla defines upgrades for a typical 220 m^2 home in Oshkosh, WI, considering different insulation approaches for pre- and post-1980 constructions (Z. Berzolla, Meng, et al., 2023). Costs are applied to all pre- and post-1980 buildings, respectively, agnostic to building size or dimensions. The *Energy Efficiency* package includes air sealing, LED lighting, Energy Star appliances, and insulation separately defined insulation upgrades for pre- and post-1980 constructions. The typical pre-1980 construction in Oshkosh is assumed to have empty wall cavities; thus, the insulation upgrade definition includes blown-in cellulose as well as a 2inch (5cm) layer of polystyrene foam board (XPS). For the typical post-1980 construction, a simple addition of a continuous XPS insulation layer is proposed. The cost for each upgrade package is calculated using RSMeans 2020 data and the NREL REMDB, described in Table 2 (Gordian, 2020; NREL REMDB, 2018). For the heat pump costs in the *Energy Efficiency and Heat Pump Installation* package, we use the *static heat pump* model to for a more accurate comparison with heat pump cost components of other models are Massachusetts-based.

Table 2. Summary of static model cost inputs for Oshkosh, WI.

Package	Upgrades	Pre-1980 (USD)	Post-1980 (USD)	Source
Energy Efficiency	Air Sealing	$925	$925	*RSMeans 2020*
	Insulation	$13,897	$12,334	*RSMeans 2020*
	LED Lighting	$200	$200	*NREL REMDB*
	ENERGY STAR Appliances *(Includes refrigerator, dishwasher, and washing machine)*	$1,650	$1,650	*NREL REMDB*
Heat Pump	Air Source Heat Pump	$18,400	$18,400	*MassCEC WHHP*
Photovoltaics	Photovoltaics	$17,137	$17,137	*NREL Solar Market Analysis 2021*

For the dynamic models, we apply the proposed dynamic model framework with the same cost inputs as the static model translated into dynamic components for consistency in this initial test. Insulation and air-sealing costs per unit area of material are outlined in Table 3. Equipment and lighting cost inputs are included in Table 4. For equipment, we apply the same inputs used by Berzolla in the static model as unit costs for ENERGY STAR appliances based on the NREL Residential Energy Measures Database (REMDB) (NREL REMDB, 2018). For lighting, a floor area cost component is assigned based on the NREL REMDB upgrade to LED lighting with a 1.5 LPD.

Table 3. Dynamic Model Cost Inputs for Weatherization (Insulation and Air-Sealing)

Upgrade	**Envelope Cost** *($/m^2)*	**Roof Cost** *($/m^2)*	**Footprint Cost** *($/m^2)*
Cellulose-Wall	$90.00	0	0
XPS-Wall	$71.12	0	0
Cellulose-Attic	0	$16.24	0
XPS-Floor	0	0	$17.12
Air Sealing	$4.20	0	0
Source	*RSMeans 2020*	*RSMeans 2020*	*RSMeans 2020*

Table 4. Dynamic Model Inputs for Lighting/Equipment

Upgrade	**Unit Cost** *($USD)*	**Floor Area Cost** *($/m^2)*
Lighting Replacement with 100% LED	0	$0.90
ENERGY STAR Refrigerator	$510	0
ENERGY STAR Dishwasher	$405	0
ENERGY STAR Washing Machine	$735	0
ENERGY STAR Dryer	$760	0
Source	*NREL REMDB*	*NREL REMDB*

The heat pump cost components for each of the dynamic models utilize those with corresponding names defined in Section 2.3— *static, NREL REMDB area-based, area-age based.* Photovoltaic upgrades included in the *Energy Efficiency, Heat Pump Installation, and Photovoltaics* package utilize the NREL solar market benchmark for 2021, as described in Section 2.2 (NREL, 2024). A summary of the four cost models is included in Table 5.

Table 5. Summary of Building Upgrade Cost Models for Oshkosh, WI

Model	**Cost Predictions** *(by upgrade type)*				**Input Data Source**
	Energy Efficiency *(EE)*		**Heat Pump** *(HP)*	**Photovoltaics** *(PV)*	
Type	***pre-1980***	***post-1980***			
Static	\$16,672 *unit*	\$15,109 *unit*	\$18,400 *unit*	\$17,137 *unit*	*US-national costs:* NREL REMDB RSMeans (2020)
Dynamic					
NREL REMDB based	\$2,410 *unit cost* \$90.42/m^2 *envelope area* \$6.89/m^2 *roof area* \$13.64/m^2 *floor area* \$16.14/m^2 *footprint area*	\$2,410 *unit cost* \$33.37/m^2 *envelope area* \$6.89/m^2 *roof area* \$13.64/m^2 *floor area* \$16.14/m^2 *footprint area*	\$630 *unit* \$85/kBtuh *load* \$1800 *per zone*	*NREL Solar Market Analysis 2021*	*US-national costs:* NREL REMDB
Area based	\$2,410 *unit cost* \$90/m^2 *envelope area* \$16.24/m^2 *roof area* \$5.10/m^2 *floor area* \$17.12/m^2 *footprint area*	\$2,410 *unit cost* \$71/m^2 *envelope area* \$16.24/m^2 *roof area* \$5.10/m^2 *floor area* \$17.12/m^2 *footprint area*	\$120/m^2 *floor area*	*NREL Solar Market Analysis 2021*	*US-national costs:* NREL REMDB RSMeans (2020) *MA regional costs:* MassCEC ASHP Pilot
Area-Age based	*(Same inputs as area-based)*		*Linear regression with two parameters: age and area*	*NREL Solar Market Analysis 2021*	*US- national costs:* NREL REMDB RSMeans (2020) *MA regional costs:* Mass Save®

We then conduct a *willingness to pay* analysis based on the model developed by Berzolla and De Simone et. al. to explore the impact various cost prediction approaches may have on the economic feasibility of different upgrade packages (Z. Berzolla et al., 2024). This methodology was based on a survey conducted by Berzolla et. al. on 1,000 homeowners in the Northeastern U.S identifying key factors influencing a homeowner's decision to upgrade (Z. Berzolla, Meng, et al., 2023). Key factors found in this survey include the upfront cost, income, and concern about emissions from their home. The *willingness to pay* model developed by Berzolla and De Simone stochastically determines if the homeowner for a given home in the Oshkosh UBEM will "upgrade" or "not upgrade", based on the upfront cost of the upgrade package, their income determined by census block, and a stochastically assigned concern factor (Z. Berzolla et al., 2024). The resulting carbon emissions reduction potential of each upgrade package is also determined, based on the homes that "upgrade". With upfront costs being a key factor, we compare the willingness to pay predictions corresponding with the upfront costs predicted for each of the three upgrade packages by the four cost models.

3. Results

3.1. *Evaluating Heat Pump Cost Models for Realistic Cost Prediction*

Costs predicted by each model are plotted against real project costs for the Mass Save® program dataset, with ideal case indicated as the identity line in Figure 3.1. Mean absolute percentage error (MAPE) is used as an indicator of performance, with a higher percentage indicating higher accuracy. The sum of predicted costs sample-wide from each model are displayed in Figure 3.2, we see that the *area-age based* model has the highest accuracy of the models tested.

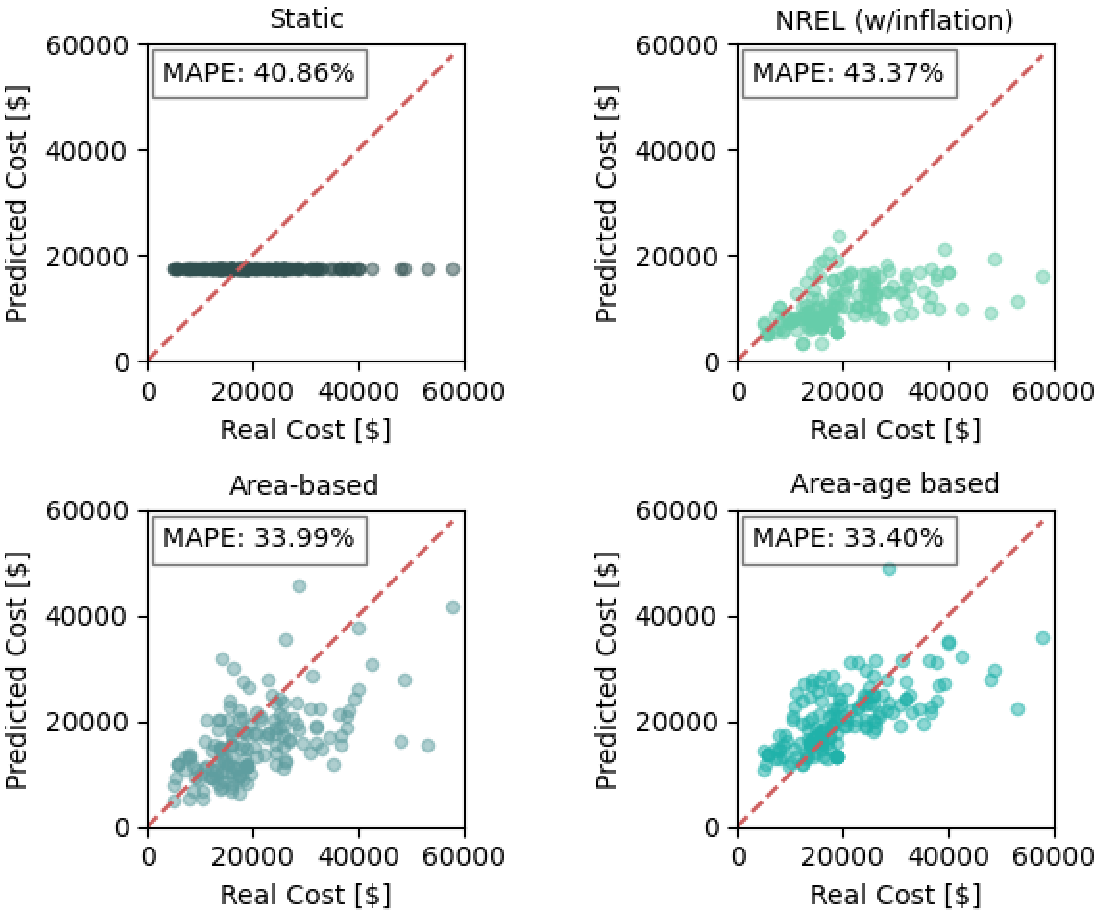

Figure 3.1. Comparison of different heat pump cost models in predicting realistic costs. Predicted and real costs are compared, with the red line indicating an ideal agreement. The mean absolute percentage error (MAPE) is shown as a metric of model performance. NREL REMDB predictions are adjusted with an inflation factor of 1.3.

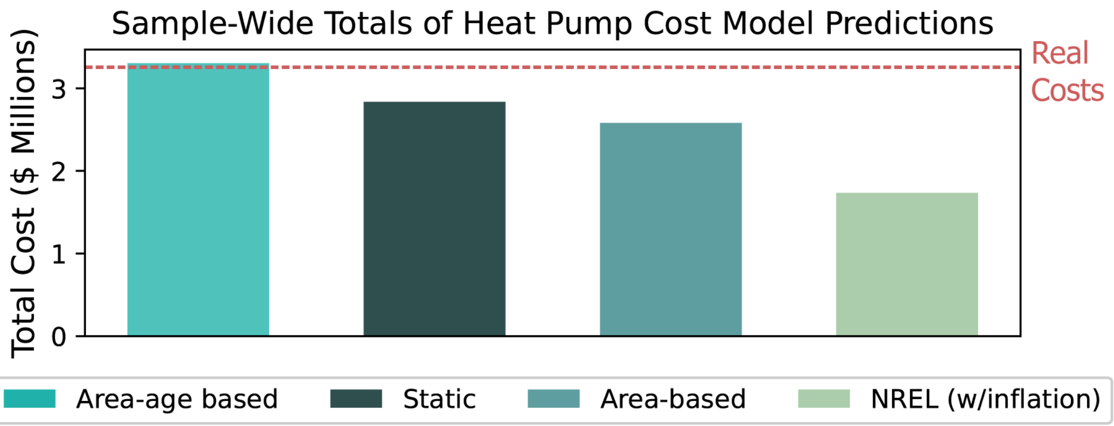

Figure 3.2 Sample-wide totals for heat pump cost model predictions.
The sum of predictions across the sample of 160 homes is shown for each of the four heat pump cost models. The real costs are included as a red dashed line for reference.

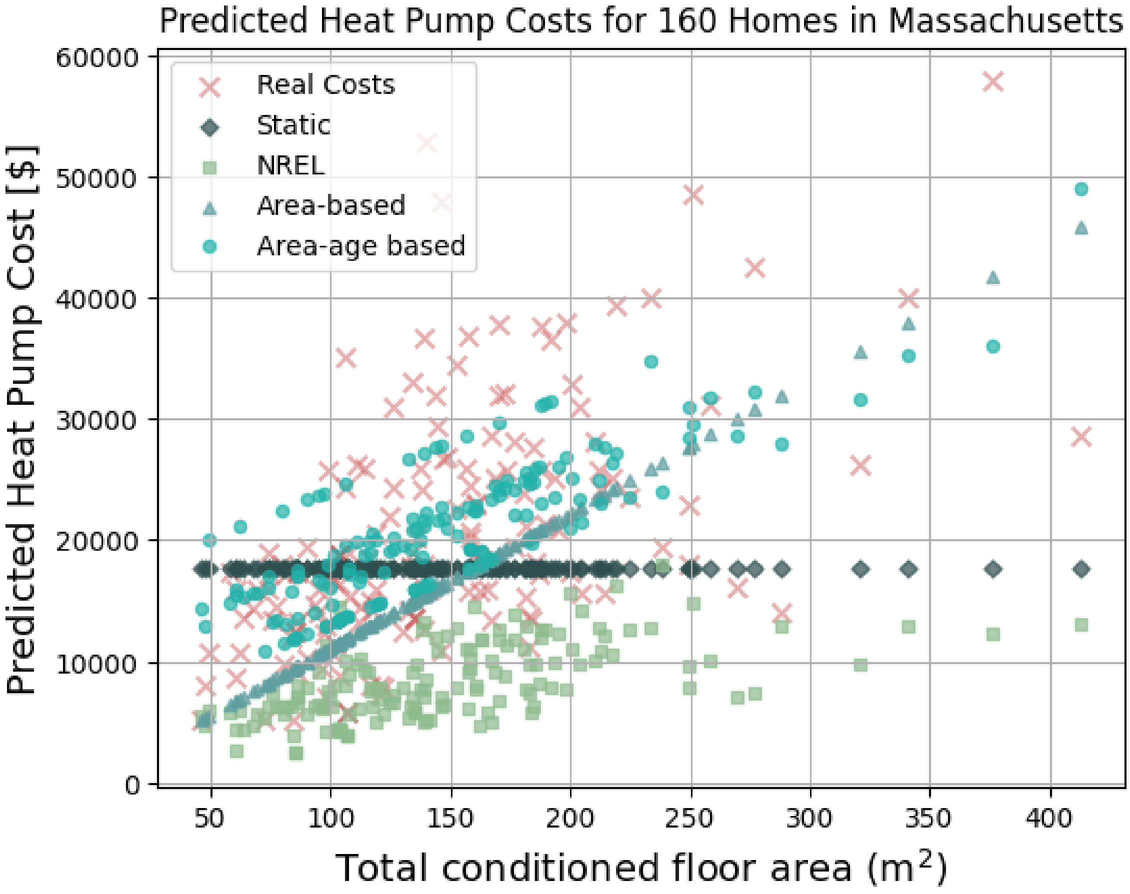

Figure 3.3. Model predictions for heat pump project costs for residences in Massachusetts. Each model is used to predict the total installed cost of heat pump for each residence in the Mass Save® dataset. The costs are plotted by total conditioned floor area to show that how the model predictions do not fully capture the real distribution of costs included for reference.

In Figure 3.3, the predictions for each project are plotted by total conditioned floor area of the home. Real costs are included as a reference to ground truth. The *area-based* model, linear by square foot, does not reflect the variation observed in the real project costs. Predictions with the *NREL REMDB* model host a more realistic variation in costs, though the vertical spread of the distribution does not match that of real project costs. As expected, the scatter of *area-age based* model cost predictions aligns most closely with that of real project costs.

3.2. Enhancing Willingness-to-Pay Predictions with Cost Models in Oshkosh, WI

City-wide total costs predicted in Oshkosh for the three upgrade packages defined in Section 2.3 are shown in Figure 3.4. For the *Energy Efficiency* Package, the *static* model shows the highest cost prediction for the city and the *NREL REMDB* model shows the lowest. The *area-based* and *area-age based* models share the same approach for energy efficiency measures, and therefore show no variation. When we look at packages with heat pump upgrade, we see that the dynamic models surpass the static model city-wide predictions, with area-based model predictions yielding the highest cost predictions. Photovoltaics show similar differences in the dynamic models because the same cost model for photovoltaics is used across all dynamic models.

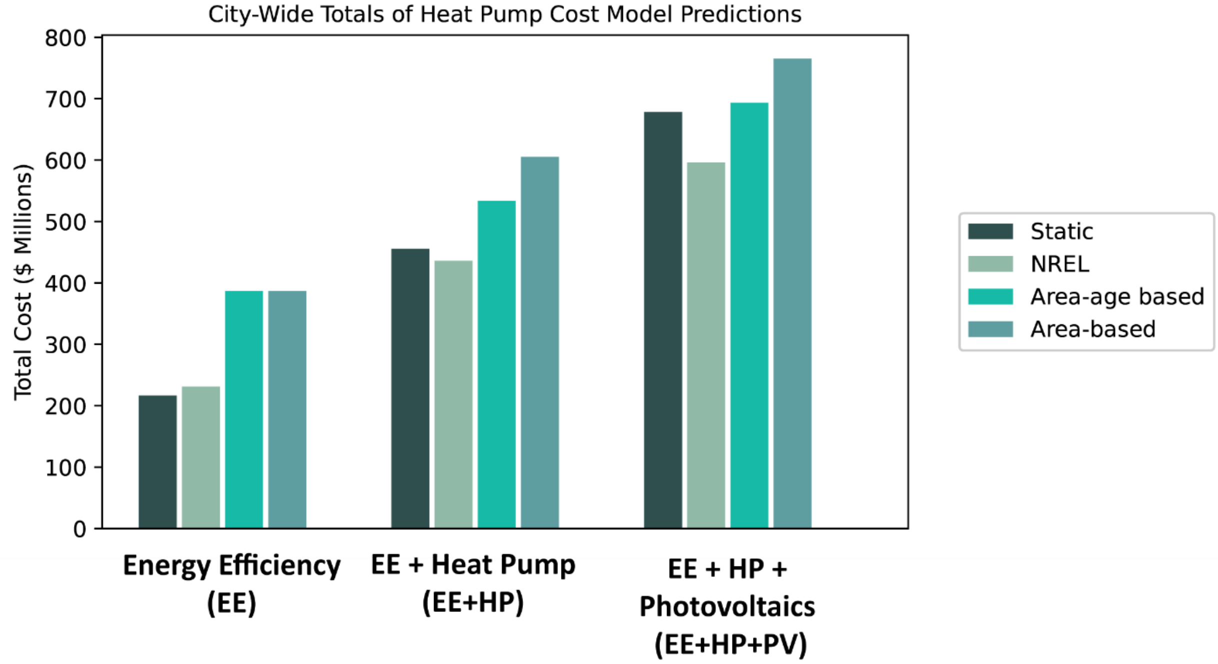

Figure 3.4. A comparison of city-wide total cost predictions for three upgrade packages. Packages include *Energy Efficiency; Energy Efficiency and Heat Pump Installation;* and *Energy Efficiency and Heat Pump Installation*. The *area-based* and *area-age* based models use the same approach for the energy efficiency predictions, and all dynamic models use the same cost predictions for photovoltaics.

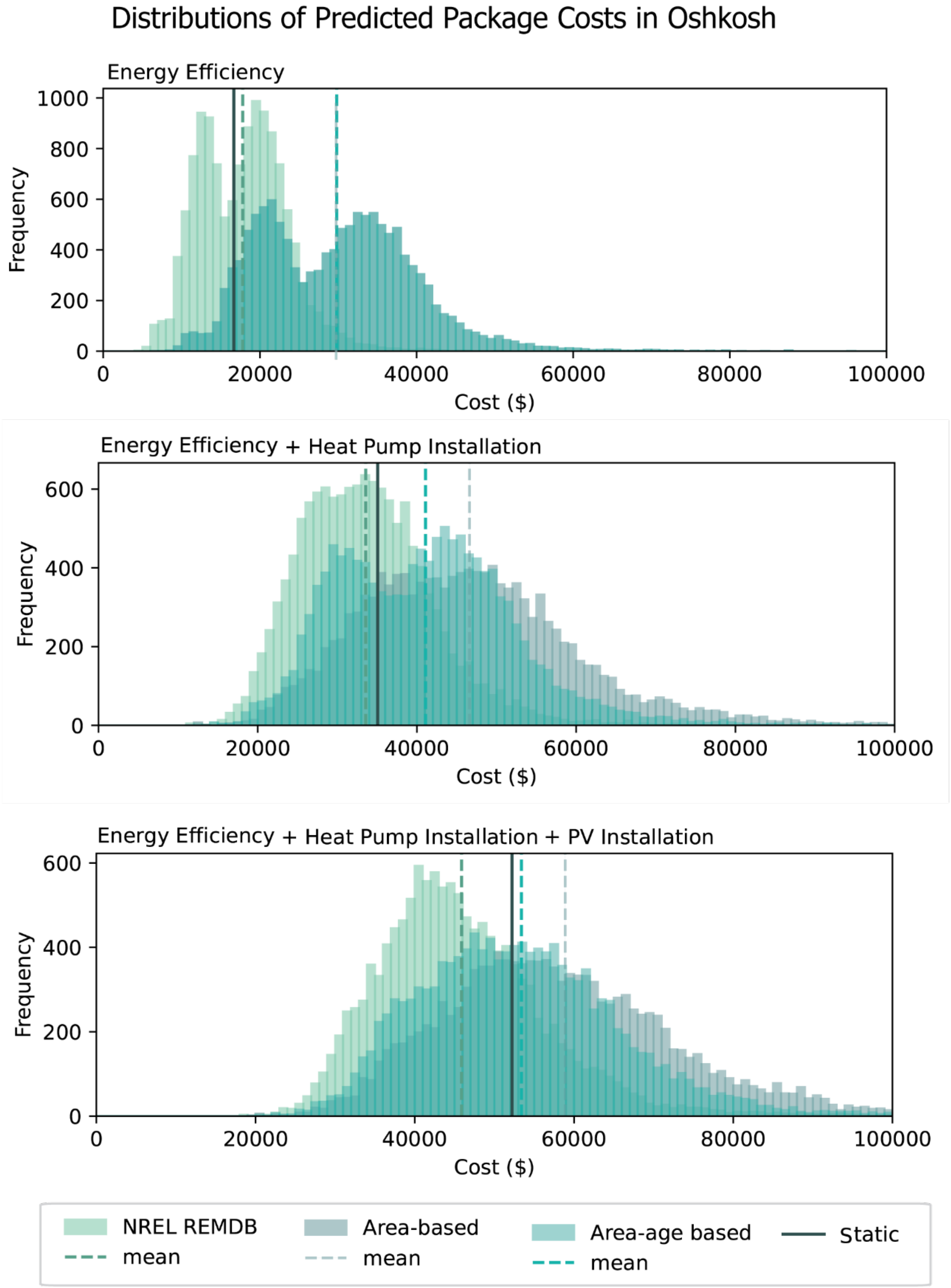

Figure 3.5. Distribution of upgrade package cost predictions across Oshkosh.

For energy efficiency, the area-based and area-age based models use identical approaches. The mean averages of predicted costs are shown as vertical dashed bars. The static model prediction is included as a reference to show the relative distributions of all models.

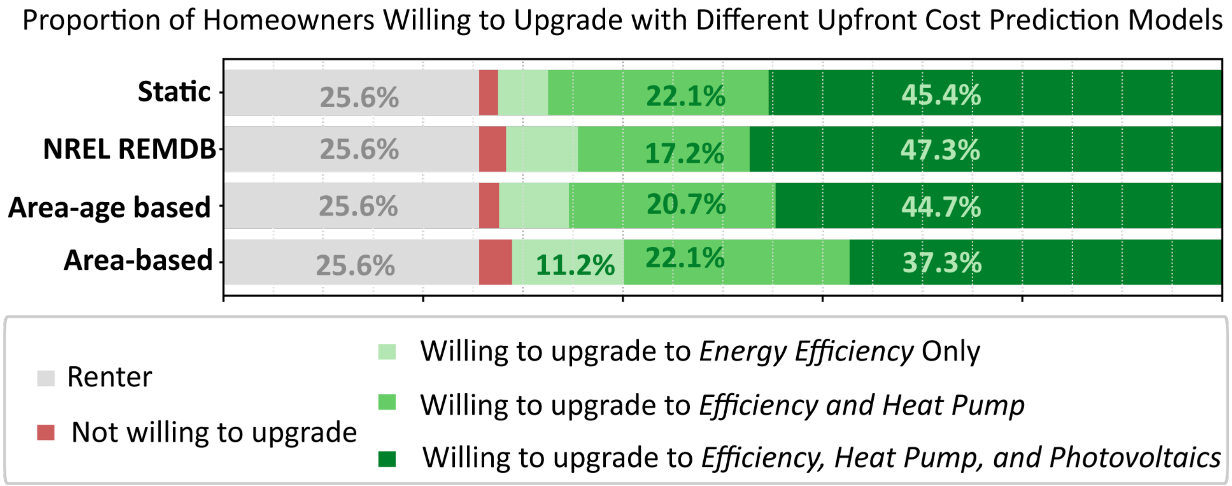

Figure 3.6. Impact of upfront cost model predictions on willingness to pay in Oshkosh. The proportions of homeowners in Oshkosh willing to pay for upgrades are shown. The percentage of renters, who can take no action and are excluded from these predictions, are shown in gray. The red shows the percentage of homeowners not willing to upgrade at all. The percentage of homeowners willing to upgrade their home with a given package are shown.

Table 5. Predicted Emissions Reductions Resulting from Different Cost Model Predictions

Cost Model	**Emissions Reductions Observed Post-Upgrade** *(% of Baseline)*
Static	61.3%
NREL REMDB	60.2%
Area-based model	60.0%
Area-age model	57.9%

For upgrade-level predictions, distributions of predicted costs per home vary among the different dynamic models as expected. For the *Energy Efficiency* upgrade package, both *area-based* and *NREL REMDB* models exhibit a higher mean predicted cost than the *static* model. For *Energy Efficiency and Heat Pump Installation* package cost predictions, the *area-based* model predictions hosts the highest mean cost and the *NREL REMDB* model hosts the lowest of the dynamic models predictions. This is expected from the heat pump model results in Section 3.1.

When comparing *willingness to pay* predictions, a 10% decrease is observed between upfront costs the *static* and *area-based* cost models in the proportion of homeowners willing to pay for of the highest tier upgrade package, *Energy Efficiency and Heat Pump Installation, and Photovoltaics*. The resulting impact on emissions of the city post upgrade adoption is approximately 4% less emission reductions than anticipated with the *static* cost model predictions. Further commentary on these results along with accompanying thoughts from the author are included in detail in the next section.

4. Discussion

As the results for the Oshkosh UBEM application in Section 2.3 suggest, the proposed dynamic upgrade cost model has a clear impact on cost predictions for city-wide building upgrade initiatives. Even in a town like Oshkosh, which embodies the essence of middle America with its typical residential buildings, accounting for specific building characteristics in cost projections can significantly influence the economic viability of proposed upgrade strategies. Through inaccurate building upgrade cost predictions, the city runs the risk of greatly over- or under-estimating the cost for given decarbonization pathways. For example, in the case of the *Energy Efficiency* package, the difference between the *static* and the *area-based* cost model predictions is upwards of $30 million of over-estimated costs. Money allocated for incentives towards these upgrades could be better allocated through improved predictions. On the other end, using the *static heat pump* model also has the potential to greatly underestimate cost. In the case of the *Energy Efficiency and Heat Pump* package, a difference of almost $200 million is observed between *static* and the more realistic *area-age based* model cost predications for city-wide upgrades. To put this in perspective, the capital investment for a heat pump upgrade across all homes in a city could exceed the $169 million heat pump technology initiative from the U.S. Department of Energy (Amarnath, 2023). For a city that has limited resources to support these pathways, the difference of a hundred million dollars of capital required to upgrade their residential building stock is significant. This is also just one city with only 13,000 American residences. When this discrepancy in cost predictions is scaled to the whole residential building stock of 144 million housing units, the difference in predictions from different cost models becomes astronomical, at almost $2.2 trillion dollars of potential *under-estimated* costs (U.S. Census Bureau, 2024). While no claims can be made on which cost may be more accurate due to the lack of real project data at the local level, the magnitude of this difference further drives the issue that improved cost inputs at the regional and local scale are vital to providing more realistic upfront cost predictions.

This especially becomes important when we keep in mind who will be paying for these upgrades: the homeowner. Our analysis using the Berzolla De Simone *willingness to pay* model in Section 3.2 reveals a notable discrepancy in predictions of homeowners willing to invest in upgrade packages featuring heat pumps. Employing the improved *area-age based* cost model, a

10% decrease in the number of homeowners willing to invest in the *Energy Efficiency, Heat Pump, and Photovoltaics* package is observed, as compared to predictions using from the *static* cost model. Seemingly modest, this translates to approximately 1,000 households opting for the medium tier *Energy Efficiency and Heat Pump Installation* upgrade package with a more accurate upfront cost assessment. In the context of the city, the resulting impact is a 4% shortfall in projected emissions reductions. These predictions assume all homeowners willing to pay follow through and upgrade their homes. Keeping in mind the unpredictability in human nature, this may be an even grosser underestimation, with even fewer homeowners following through with heat pump installation projects. This means that, with more realistic cost predictions, an identified technological pathway could yield potentially even less of an impact on the emissions reductions expected. Further driving the issue that technological pathways are not sufficient on their own; economic feasibility of upfront costs must also be considered in the development of decarbonization pathways.

In a 2021 study by Less et. al. at the Lawrence Berkeley National Laboratory (LBNL) Building Technologies Division, the costs of decarbonization measures were investigated for cost drivers, energy savings potential, and potential for impact in the building decarbonization strategy (Less et al., 2021). However, for a national study, the only data able to be acquired was a small data set of real project data for 1,739 projects, from 15 states and 12 energy programs for a total of 10,512 individual measures. Almost all project cost data acquired for the study fell under the total cost category, with effectively no detail on labor and material breakdowns. The inaccessibility of real project costs with detailed recording of sub costs and building-level characteristics poses a significant challenge in weighing cost factors in the development of an improved cost model approach for these upgrades. As we see in the breakdown of total project costs for the Mass Save whole-home air source heat pump program data (Figure 2.2), both system hardware costs and soft costs (i.e. labor and administration) vary significantly across projects, with no clear tie to any two or three building metrics. While the LBNL study and this work start to unpack the complexity and underlying factors that influence installation costs, data availability continues to be a challenge for analysis in the area. Data collections must be ramped up significantly to provide the best-informed guidance for deployment efforts, including strategic planning, policy development, and efficiency program fund allocation.

While efficiency programs may have a clear schedule of rebates they are willing to award for given home renovations, the correlation between these costs and the actual costs needed to incentivize homeowners to pursue home renovation projects is not always clear. Millions of dollars are being devoted to rebate and incentive programs to encourage increased adoption of building retrofits by homeowners. Current efficiency programs implement either a static cost approach or simple dynamic approaches to quickly assign rebates and incentives for specific building retrofit measures. For example, Efficiency Vermont offers up to 75% coverage of weatherization projects completed by certified contractors for Vermont residents who qualify (Efficiency Vermont, 2024). However, if a homeowner decides to complete do-it-yourself (DIY) weatherization measures, only a static rebate of $100 is awarded (Efficiency Vermont, 2024). In comparison to costs estimated by the *area-based* model, mean upfront costs of weatherization upgrades are in the range of $7000. This is a significant investment for homeowners falling in low- and medium-income groups, even with a discount of $100. While low-income groups may be eligible for further assistance by state and federal level programs, many homeowners falling just above the threshold still face significant upfront costs for these “low-cost” upgrades. When we consider higher cost upgrades, such as heat pumps, this becomes even more of an issue, as we saw in the willingness to pay analysis for Oshkosh in Section 3.2. When we consider incentives in Massachusetts for homeowners installing air source heat pumps, Mass Save® provides a rebate of up $10,000 per home (MassSave, 2024). This is either a static, fixed rebate of $10,000 when the heat pump is the sole source of heating and cooling, or as a load-based cost of $1250 per ton of capacity (up to $10,000), for homeowners who decide to simply supplement their existing system with a ASHP (MassSave, 2024). When comparing this to real project installation costs from MassSave, costs can range up to $55,000 for a single project. While the homeowner was willing to pay in the case of this real project, lower income customers may not be willing to pay, even with the available incentives. By improving upgrade cost predictions through dynamic models, such as the one proposed in this work, we enable a more realistic understanding of the upfront costs homeowners are facing. This in turn allows for better allocation of limited funds and the development of frameworks for equitable incentive allocation, as discussed in work by De Simone (De Simone, 2024), and potential financing strategies for low-income homeowners who face significant energy burden, as discussed by Moore (Moore, 2024).

While upfront cost are a significant barrier to adoption for many homeowners, it is only one factor of many influencing a homeowner's decision to act. In discussions with efficiency programs, there is still a struggle in influencing homeowners to retrofit their homes, despite some of them being free or minimal cost to qualifying residents. For example, the Vermont Weatherization Assistance Program provides free weatherization services to residents who qualify based on income threshold requirements. However, a small percentage of homeowners who qualify are pursuing these free services. As found by Berzolla in the development of the *willingness to pay* model, many other factors contribute, including concern for the environment, education, energy burden, whether their neighbor has upgraded (Z. Berzolla, Meng, et al., 2023). The confusion around the countless programs for rebates and incentives available and uncertainty around which package of upgrades may be right for them also greatly influence a homeowner. However, the field has struggled to provide a better answer than "it depends" when it comes to answer the questions homeowners have around how much a given upgrade package may cost and how long until energy savings from a given upgrade recoup the initial investment. A recent Green Upgrade Calculator developed by the Rocky Mountain Institute (RMI) gets a step closer to helping answer this question (Rocky Mountain Institute, 2024). The tool leverages the NREL REMDB and RS Means input costs. With the availability of more robust models that capture the nuances of building upgrade costs at the local and regional level, tools such as this one hosts the potential for significant impact on improving retrofit adoption through improved homeowner education around cost- and non-cost benefits of building upgrades.

An additional factor contributing to the lack of adoption rates is the availability of qualified contractors to complete the work required for specific upgrade measures, especially in rural regions. In a study by the National Renewable Energy Laboratory (NREL), the building industry workforce faces challenges that extend beyond just gaps in technical skills; social and environmental challenges are also at play (Truitt et al., 2022). In response to this issue, leading efficiency programs are developing contractor networks with supporting training opportunities. Notable examples include the Efficiency Vermont's Energy Action Network (EAN) and the Southern California Regional Energy Network (SoCalREN) (Efficiency Vermont, 2024b; SoCalREN, 2024). In the case of SoCalREN, local programs in rural and hard to reach regions, such as the High Sierra Energy Foundation (HSEF), have initiated a partnership that hosts local workforce development programs (High Sierra Energy Foundation, 2023). While these local and regional initiatives are a great start, they are few and far between. Increased efforts are required for the development of an effective workforce needed to complete the work necessary for decarbonizing the building sector.

In the case of heat pumps, contractor behavior could be a driving factor in why homes with similar characteristics in the same region still host vastly different installation costs, as shown in Table 6. These factors could include learning curves of heat pump installers, influences rebate programs have on contractors in sizing the heat pumps, as explored by Ontiveros (Ontiveros, 2024). In a study of heat pump sizing for project installations for MassCEC and Mass Save rebate program customers, Ontiveros found that installers for Mass Save rebate customers generally "over-size" heat pumps, whereas MassCEC installers generally "under-size" heat pumps. This corresponds with the structure of each program, where Mass Save incentivizes full heating system replacement and MassCEC allows homes to keep their backup heat (Ontiveros, 2024). While oversizing could have its benefits for central ducted variable capacity (VC) systems by increasing the efficiency of the system by as much as 43%, as explored by Cummings et. al., the system size is a significant driver in the upfront cost (Cummings & Withers, 2014). Additional factors influencing cost variations between similar projects could also include technical skill gaps, such as whether the electrical upgrade needed in some projects needs to be outsourced due to lack of electrical training, which increases costs. The income status of the customer, value of the home, the distance from the installer's office or main roads, or the need for other special equipment to address a more complex home geometry, may also have influences on costs.

While the *area-age based* model offers a significant improvement over simple dollars per square foot estimations, it still greatly underestimates the real cost of some installations, as in the case of Building A (Table 6). This underestimation could potentially extend to other complex upgrades as well. As in the case of this study, the lack of available of real project cost data limited façade upgrade cost estimations to an *area-based* in this dynamic cost model. However, as we saw with heat pump installations, the development of a more robust cost models could be possible with access to more real project data. Thus, more-detailed real project cost data and potentially additional residential data (e.g. additional GIS data or real estate databases) that can be integrated into the UBEM framework is required to further improve upgrade cost model predictions.

Table 6. Comparison of real project costs between similar residences in Massachusetts.

Building Characteristics	**Building A**	**Building B**
Total conditioned floor area	146 m^2	180 m^2
Estimated year of construction	Before 1900	1910-1919
Housing Type	Attached single-family *2 unit*	Attached single-family *2 unit*
Cost Model Predictions		
Static	$18,400	$18,400
NREL REMDB	$7,080	$8,880
Area-based	$17,520	$21,600
Area-age based	$32,206	$25,927
Real Cost	$48,000	$18,200

This analysis only scratches the surface of providing more realistic predictions for building upgrade costs at the urban level. While a dynamic approach such as the one proposed in this paper has the potential to provide more realistic cost predictions than static models, the accuracy of these predictions to real costs is only as good as the input costs. Ultimately, we live in an economics driven world; costs of material, labor, and equipment are constantly changing with the ebb and flow of their relative economic markets. Renewable energy generation, including wind, solar, geothermal, and hydropower and battery storage technology costs are addressed at commercial and residential scales through the NREL Annual Technology Baseline (ATB) (NREL ATB, 2021). The residential PV market is even more thoroughly studied by ongoing research efforts by the Solar Market Research & Analysis group at NREL, providing quarterly market reports of the solar industry (NREL, 2024). This type of ongoing market analysis efforts should be extended to other technologies that are key in the building decarbonization efforts like heat pumps. Only with these market-informed input costs and a deeper understanding of the behavioral economic drivers behind building renovation projects do such cost model predictions become meaningful. Only then can the dynamic upgrade cost model approach infuse the well-established methods of physics-based urban building energy modeling with economics-based costs, thus empowering cities with techno-economically feasible building decarbonization pathways.

5. Conclusion

While urban building energy modeling research efforts have developed robust, physics-based simulation frameworks to define city-scale technology pathways toward climate goals, a crucial question in making these pathways actionable has been largely neglected: *how much does it really cost?* The scarcity of contemporary source data available and currently available methods for cost estimation at the urban scale makes this question difficult; further questions around equitable incentive programs are nearly impossible to answer.

In this study, several approaches to integrating upfront costs into the urban building energy modeling (UBEM) framework are compared. The dynamic upgrade cost model proposed provides the mechanism for more realistic predictions of upgrade costs, which directly impacts predictions on homeowner adoption of different building upgrade packages. These improved cost predictions around building upgrade strategies for decarbonization efforts have the potential to inform effective fund allocation for more equitable incentive programs and financing strategies for low-income homeowners, such as methods developed by De Simone and Moore (De Simone, 2024; Moore, 2024). Furthermore, by integrating this dynamic upgrade cost model with accelerated energy simulation techniques for urban scale UBEM analyses, such as methods developed by Le Hong and Wolk, upgrade pathways to decarbonization can be optimized for both technical and economic feasibility (Le Hong & Wolk, 2024). In this way, the dynamic approach to cost modeling for building upgrades is a key component in supporting municipalities to develop equitable, economically feasible strategies for decarbonizing their building stock.

However, a key point this work illustrates is the real project cost data and further work needed to provide localized, market-informed input costs that make such cost model predictions meaningful. Only then can the dynamic upgrade cost model approach infuse the well-established methods of physics-based urban building energy modeling with economics-based cost predictions, thus empowering cities to achieve their climate goals with techno-economically feasible building decarbonization pathways.

6. References

Adler, A. I., & Painsky, A. (2021). *Feature Importance in Gradient Boosting Trees with Cross-Validation Feature Selection* (arXiv:2109.05468). arXiv. https://doi.org/10.48550/arXiv.2109.05468

Amarnath, N. (2023). *DOE allocates $169M to propel electric heat pump manufacturing across 13 states*. Utility Dive. https://www.utilitydive.com/news/doe-allocates-169m-electric-heat-pump-manufacturing-13-states/700596/

Ang, Y. Q., Berzolla, Z. M., Letellier-Duchesne, S., & Reinhart, C. F. (2023). Carbon reduction technology pathways for existing buildings in eight cities. *Nature Communications*, *14*(1), 1689. https://doi.org/10.1038/s41467-023-37131-6

Arrhenius, S. (1896). “On the Influence of Carbonic Acid in the Air upon the Temperature of the Ground” (1896). *Philosophical Magazine and Journal of Science*, *41*(April), 273–276. https://doi.org/10.12987/9780300188479-028

ASHRAE. (2022). *Standard 90.1*. https://www.ashrae.org/technical-resources/bookstore/standard-90-1

Auf Hamada, A., Raslan, R., & Hong, S.-M. (2023). *A framework for parametric multi-criteria decision analysis (P-MCDA) for building retrofits*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1519

Baliga, R., & Gilles, D. (2022). *Decision Support Framework for the Retrofit of Public Buildings for Energy and Carbon Reduction*. *10*, 424–431. https://doi.org/10.26868/25746308.2022.C048

Bass, B., Ezell, E., & New, J. (2022). *Using Measured Building Energy Data to Infer Building Characteristics for Urban Building Energy Modeling*. *10*, 173–180. https://doi.org/10.26868/25746308.2022.C021

Berrill, P., Wilson, E. J. H., Reyna, J. L., Fontanini, A. D., & Hertwich, E. G. (2022). Decarbonization pathways for the residential sector in the United States. *Nature Climate Change*, *12*(8), Article 8. https://doi.org/10.1038/s41558-022-01429-y

Berzolla, Z., Ang, Y. Q., Letellier-Duchesne, S., & Reinhart, C. (2023). An eight-step simulation-based framework to help cities reach building-related emissions reduction goals. *Environmental Research: Infrastructure and Sustainability*, *3*(4), 045003. https://doi.org/10.1088/2634-4505/ad025d

Berzolla, Z., De Simone, Z., & Reinhart, C. (2024). *Modeling techno-economic adoption of building energy retrofits at the city-scale* (SSRN Scholarly Paper 4810876). https://doi.org/10.2139/ssrn.4810876

Berzolla, Z. M. (2021). *Meeting A Community's Emissions Reduction Targets Using Urban Building Energy Modeling* [Thesis, Massachusetts Institute of Technology]. https://dspace.mit.edu/handle/1721.1/142856

Berzolla, Z., Meng, T., & Reinhart, C. (2023). *Homeowners' Willingness to Pay for Residential Building Retrofits* (SSRN Scholarly Paper 4536734). https://doi.org/10.2139/ssrn.4536734

Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P. W., Trisos, C., Romero, J., Aldunce, P., Barrett, K., Blanco, G., Cheung, W. W. L., Connors, S., Denton, F., Diongue-Niang, A., Dodman, D., Garschagen, M., Geden, O., Hayward, B., Jones, C., … Péan, C. (2023). *IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland.* (First). Intergovernmental Panel on Climate Change (IPCC). https://doi.org/10.59327/IPCC/AR6-9789291691647

Cluett, R., & Amann, J. (2014). Residential Deep Energy Retrofits. *Tech. Rep. A1401*. American Council for an Energy-Efficient Economy, Washington, DC, USA.

Cruz, A. S., Bastos, L. E. G., & Caldas, L. R. (2023). *Multi-objective optimization based on a surrogate model of social housing to improve the thermal-energy-carbon performance*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1214

Cummings, J. B., & Withers, C. R. (2014). Making the Case for Oversizing Variable-Capacity Heat Pumps. *ACEEE Summer Study on Energy Efficiency in Buildings*. ACEEE Summer Study on Energy Efficiency in Buildings, Asilomar Conference Center, Pacific Grove, CA.

De Simone, Z. (2024). *Developing frameworks for an equitable future: From building decarbonization to generative modeling* [Thesis, Master of Science in Building Technology]. Massachusetts Institute of Technology.

Efficiency Vermont. (2024a). *Air-to-Water Heat Pumps | Efficiency Vermont*. https://www.efficiencyvermont.com/rebates/list/air-to-water-heat-pumps

Efficiency Vermont. (2024b). *Growing the Weatherization Workforce to Help Vermont Meet Climate Goals*. https://www.efficiencyvermont.com/blog/our-insights/growing-the-weatherization-workforce-to-help-vermont-meet-climate-goals

Fennell, P. J., Korolija, I., Rawal, R., Wieser, M., & Oraiopoulos, A. (2023). *Developing teaching in urban building energy modelling*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1468

Geagea, T. L., & Saleh, P. H. (2023). *Net-zero individual housing: Investigating passive retrofitting scenario in warm mediterranean climate*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1511

Gordian. (2020). *Green Building Costs with RSMeans data*.

High Sierra Energy Foundation. (2023). *SoCalREN Multifamily Program*. High Sierra Energy Foundation. https://www.highsierraenergy.org/socalren-multifamily-program

IISD, S. K. H. (2019). *77 Countries, 100+ Cities Commit to Net Zero Carbon Emissions by 2050 at Climate Summit | News | SDG Knowledge Hub | IISD*. http://sdg.iisd.org/news/77-countries-100-cities-commit-to-net-zero-carbon-emissions-by-2050-at-climate-summit/

International Code Council. (2021). *International Energy Conservation Code*. International Code Council. https://codes.iccsafe.org/content/IECC2021P1

International Energy Agency. (2022). *An updated roadmap to Net Zero Emissions by 2050 – World Energy Outlook 2022 – Analysis*. International Energy Agency (IEA). https://www.iea.org/reports/world-energy-outlook-2022/an-updated-roadmap-to-net-zero-emissions-by-2050

International Energy Agency. (2023). *World Energy Outlook 2023*. International Energy Agency (IEA).

Ju, Y., & Moura, S. (2023). *Pricing scheme design for vehicle-to-grid considering customers risk-aversive behaviors*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1608

Kourgiozou, V., Al-Saegh, S., Korolija, I., Dowson, M., Commin, A., Tang, R., Rovas, D., & Mumovic, D. (2023). *Development of a dynamic building stock model for smart energy transition decision support: University campus stock case study*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1686

Lara Arambula, R., Carnieletto, L., & Pasut, W. (2023). *Toward a resilient campus: Analysis of university buildings to evaluate fast implementing strategies to reduce the energy consumption*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1688

Le Hong, Z., & Wolk, S. (2024). *Accelerating Urban Building Energy Modeling* [Thesis, Masters of Science in Building Technology]. Massachusetts Institute of Technology.

Less, B., Walker, I., Casquero-Modrego, N., & Rainer, L. (2021). *The Cost of Decarbonization and Energy Upgrade Retrofits for US Homes* (None, 1834578, ark:/13030/qt0818n68p; p. None, 1834578, ark:/13030/qt0818n68p). Lawrence Berkeley National Laboratory (LBNL) Building Technologies Division. https://doi.org/10.2172/1834578

Li, G., Wang, Z., & Xu, C. (2023). *A novel rooftop solar energy potential estimation method based on deep learning at district level*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1450

Lin, Y.-W., Sun, R., Schiavon, S., & Spanos, C. (2023). *Toward design automation for building models*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1709

MassCEC. (2021). *MassCEC Pilot Showcases Success of Whole Home Heat Pumps | MassCEC*. https://www.masscec.com/blog/masscec-pilot-showcases-success-whole-home-heat-pumps

MassSave. (2024). *Air Source Heat Pumps | Residential*. Mass Save. https://www.masssave.com/en/residential/rebates-and-incentives/heating-and-cooling/heat-pumps/air-source-heat-pumps

Moore, L. (2024). *Building renovation financing models for low-income homeowners* [Thesis, Masters of Science in Building Technology]. Massachusetts Institute of Technology.

NEEP. (2023). *ccASHP Specification & Product List | Northeast Energy Efficiency Partnerships*. https://neep.org/heating-electrification/ccashp-specification-product-list

Northeastern Energy Partnership. (2023). *ASHP Buying Guide for Homeowners.* https://ashp.neep.org/#!/product_list/

NREL. (2024). *Solar Installed System Cost Analysis*. https://www.nrel.gov/solar/market-research-analysis/solar-installed-system-cost.html

NREL ATB. (2021). *Annual Technology Baseline 2021.* https://atb.nrel.gov/

NREL REMDB. (2018). *National Residential Efficiency Measures Database (REMDB)*. https://remdb.nrel.gov/

Ontiveros, J. (2024). *Contractor Learning and Home Energy Efficiency in Heat Pump Installations* [Thesis, Masters of Science in Technology and Policy]. Massachusetts Institute of Technology.

Pan, D., Yu, X., & Zhou, Y. (2023). *Operational carbon footprint analysis and low-carbon design strategies of a high-rise office building in subtropical Guangzhou, China*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1648

Park, C.-H., Kim, Y.-S., Song, T. Y., Ra, S.-J., & Park, C.-S. (2023). *Causality-based model for decision-making of building energy retrofit*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1176

Piro, M., Ballarini, I., & Corrado, V. (2023). *From Building Energy Models (BEM) to Urban Building Energy Models (UBEM): Input data and modelling approaches*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1662

Purdy, K. (2022). *Heat Pumps Costs—Here's How Much Homeowners Are Paying in 2022*. https://carbonswitch.com/heat-pump-costs/

Rachman, A. P., Ichwania, C., Atthaillah, Mangkuto, R. A., & Pradipta, J. (2023). *Passive design multi-objective optimization for high-performance tropical office buildings: Comparison of four different decision-making algorithms*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1237

Reinhart, C. F., & Cerezo Davila, C. (2016). Urban building energy modeling – A review of a nascent field. *Building and Environment*, *97*, 196–202. https://doi.org/10.1016/j.buildenv.2015.12.001

Rocky Mountain Institute. (2024, April 10). *Green Update Calculator | RMI*. Green Upgrade Calculator. https://greenup.rmi.org/

Shen, X., Huang, L., Novelli, N., Singhvi, A., Zarmehr, A., Aiolova, M., & Vollen, J. (2023). *Systematizing Optioneering Approach in high performance building design*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1410

Sigrist, D., Deb, C., & Schluter, A. (2019). Cost-optimal retrofit analysis for residential buildings—IOPscience. *Journal of Physics*. https://iopscience.iop.org/article/10.1088/1742-6596/1343/1/012030

SoCalREN. (2024). *Resources | SoCalREN*. https://socalren.org/wet

Song, C., Chen, Y., Deng, Z., & Yuan, Y. (2023). *Assessing the Potential of Open Data for Expanding the Urban Building Dataset: A case study in Huangpu District, Shanghai*. *18*, 0–0. https://doi.org/10.26868/25222708.2023.1355

Truitt, S., Bean, J., Sullivan, J., Paranjothi, G., & Moe, A. (2022). *Completing the Circuit: Workforce Development for Advanced Building Construction and Grid-Interactive Efficient Buildings* (NREL/TP-5500-80480, 1855580, MainId:42683; p. NREL/TP-5500-80480, 1855580, MainId:42683). https://doi.org/10.2172/1855580

U.S. Census Bureau. (2024). *U.S. Census Bureau QuickFacts: United States*. https://www.census.gov/quickfacts/fact/table/US/HSG010222#HSG010222

U.S. Department of Energy. (2024a). *DOE Announces Better Buildings Initiative to Accelerate Heat Pump Manufacturing and Adoption, Reducing Energy Waste and Lowering Energy Bills*. Energy.Gov. https://www.energy.gov/articles/doe-announces-better-buildings-initiative-accelerate-heat-pump-manufacturing-and-adoption

U.S. Department of Energy. (2024b). *Prototype Building Models | Building Energy Codes Program*. U.S. Department of Energy. https://www.energycodes.gov/prototype-building-models

Wilson, E., Metzger, C. E., Horowitz, S., & Hendron, R. (2014). 2014 Building America House Simulation Protocols. *Renewable Energy*.

Zhao, D., & Mo, Y. (2023). Construction Cost Decomposition of Residential Building Energy Retrofit. *Buildings*, *13*(6), Article 6. https://doi.org/10.3390/buildings13061363